Dissertationes Forestales 391

Boreal forest tree species classification using uncrewed aerial vehicles

Anton Kuzmin

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

Academic dissertation

To be presented, with the permission of the Faculty of Science, Forestry and Technology of the University of Eastern Finland, for public criticism in the auditorium C2 of the University of Eastern Finland, Yliopistokatu 4, Joensuu, on 17 of June 2026, at 12 o' clock noon.

Title of dissertation: Boreal forest tree species classification using uncrewed aerial vehicles
Author: Anton Kuzmin

Dissertationes Forestales 391
https://doi.org/10.14214/df.391

Thesis supervisors:
Professor Matti Maltamo
School of Forest Sciences, University of Eastern Finland, Finland

Associate Professor Lauri Korhonen
School of Forest Sciences, University of Eastern Finland, Finland

Professor Timo Kumpula
Department of Geographical and Historical studies, University of Eastern Finland, Finland

Pre-examiners:
Associate Professor Langning Huo
Swedish University of Agricultural Sciences

Lecturer Martin Mokroš
University College London

Opponent:
Professor Krzysztof Stereńczak
Department of Geomatics, Forest Research Institute, Poland

ISSN 1795-7389 (online)
ISBN 978-951-651-872-8 (pdf)

Publishers:
Finnish Society of Forest Science
Faculty of Agriculture and Forestry of the University of Helsinki
School of Forest Sciences of the University of Eastern Finland

Editorial Office:
Finnish Society of Forest Science
Viikinkaari 6, FI-00790 Helsinki, Finland
https://www.dissertationesforestales.fi

Kuzmin, A. (2026) Boreal forest tree species classification using uncrewed aerial vehicles. Dissertationes Forestales 391. 38 p. https://doi.org/10.14214/df.391

ABSTRACT

Accurate tree species classification plays a central role in forest management, biodiversity monitoring, and ecological research. In boreal environments, the relatively low species diversity and simple canopy structure offer favorable conditions for species-level analysis using remote sensing. However, classification remains challenging due to structural heterogeneity and the scattered distribution of ecologically significant broadleaved species such as European aspen. This dissertation evaluates the potential of uncrewed aerial vehicles (UAVs) equipped with RGB, multispectral (MSP), and LiDAR sensors to classify tree species and detect key biodiversity indicators in boreal forests of Finland.

The research is based on four sub-studies conducted in boreal conditions using various UAV platforms and sensor configurations, including helicopter-based RGB imagery, photogrammetric point clouds, and UAV-mounted LiDAR. Tree species included in classifications were Scots pine (*Pinus sylvestris* L.), Norway spruce (*Picea abies* (L.) Karst.), birches (*Betula pendula* Roth, *B. pubescens* Ehrh.), and European aspen (*Populus tremula* L.). Classification methods included linear discriminant analysis (LDA), support vector machines (SVM), and random forest (RF), using features derived from spectral, structural, texture, and shape attributes.

The highest classification accuracy (OA = 95%) was achieved using early-season multispectral imagery combined with manually delineated crown segments. However, automatic segmentation using RGB-derived point clouds also performed strongly, achieving 92% overall accuracy and a kappa coefficient of 0.90. Integrating structural and spectral information, particularly when acquired simultaneously, consistently improved classification outcomes. The methods also proved effective in identifying ecologically important elements such as European aspen and standing dead trees, with F1-scores for aspen reaching up to 97%.

The results further show that seasonal conditions significantly influence classification accuracy, with early phenological stages providing optimal spectral separability. Feature importance analyses underscored the value of combining spectral, structural, and textural information to maximize classification performance. While multi-sensor setups offered the highest accuracies, well-executed single-sensor approaches still produced reliable results under favorable conditions.

This thesis demonstrates that UAV-based remote sensing offers a cost-efficient, high-resolution alternative to field inventories in tree species classification and biodiversity assessment. The findings support the development of flexible, operational workflows tailored to boreal forest conditions and biodiversity monitoring needs, advancing the role of UAV technologies in sustainable forest management.

Keywords: drone, biodiversity, European aspen, LiDAR, multispectral, deadwood

ACKNOWLEDGEMENTS

When I first started this dissertation, I did not expect the journey to become quite this long. It lasted through several research projects, many field campaigns, countless manuscript versions, and even a period away from academia. I am deeply thankful to everyone who supported, guided, encouraged, and pushed me forward along the way.

I would like to sincerely thank my supervisors, Matti Maltamo, Lauri Korhonen, and Timo Kumpula, for their support throughout this work. Matti, thank you for your trust, support, and guidance during this long process. Lauri, I especially appreciate how you guided me from the very beginning, introduced me to the world of science and research, shared ideas, and answered my endless questions. Timo, I am also deeply grateful for the many field campaigns we carried out together over the years, the freedom and full trust you gave me in drone-based research, and your continuous support throughout this dissertation.

I wish to express my appreciation to the pre-examiners of this thesis, Associate Professor Langning Huo and Dr. Martin Mokroš, for their careful reviews, constructive comments and valuable suggestions. I also warmly thank Professor Krzysztof Stereńczak for kindly agreeing to act as my opponent in the public examination of this thesis. I acknowledge the School of Forest Sciences for providing the academic home for my doctoral studies, and the Department of Geographical and Historical Studies, where I carried out much of my research work over the past years. I warmly thank Alfred Colpaert and Pieter Dhondt for their support during important stages of this journey.

I would also like to warmly thank my co-authors and colleagues involved in the IBC-Carbon project (project no. 312559). Petteri, Topi, Sonja, Sarita, Pekka, Janne, Laura, Arto, Aleksi and Max, thank you for the many long field days, memorable moments and more tree measurements than I would like to count. I sincerely thank Alwin A. Hardenbol and Mikko Kukkonen, for their valuable collaboration. I also want to thank Arbonaut Oy, where my period away from academia gave me valuable insight into the practical side of forest inventory. My sincere thanks go to Tuomo Kauranne, Jussi Peuhkurinen and Alain Minguet for their support and for sharing their deep practical knowledge of forest inventory.

I would also like to thank my friends, who made this journey easier and more meaningful. I am especially grateful to Pasi Korpelainen, a true brother-in-arms. Through many UAV platforms, sensors, field campaigns, technical problems, and practical lessons, we gained a great deal of experience together, and Pasi helped me become the drone pilot I am today. My old friends Sergey Senko and Maxim Trishkin deserve special thanks for being by my side throughout this long journey. During this PhD path, I was lucky to meet people who became much more than colleagues and I warmly thank Miguel Villoslada, Franziska Wolff, Mariana Verdonen, Aleksander Osipov, Teemu Tahvanainen, Tiina Kolari and Thaisa Bergamo for all the laughs, deep talks, support, and friendship during these years.

Finally, I would like to thank my family. I owe so much to my parents, Svetlana and Aleksander, for their love, support, and belief in me throughout my life, and to my “big sista” Julia for her love and support over the years. Of course, my warmest thanks also go to my lovely grandmother Valentina for her love, kindness, and care. Most importantly, I want to thank my children, Mark and Olivia, who have been the centre of my life during this journey. No matter how much I love my work, the best part of all the field trips and conferences around the world was always coming home to your hugs. This thesis is also for you.

Joensuu, 2026 Anton Kuzmin

LIST OF ORIGINAL ARTICLES

This thesis is based on the following research articles, referred to by the Roman Numerals **I-IV**.

I. Kuzmin A, Korhonen L, Manninen T, Maltamo M (2016) Automatic Segment-Level Tree Species Recognition Using High Resolution Aerial Winter Imagery, European Journal of Remote Sensing, 49:1, 239-259, https://doi.org/10.5721/EuJRS20164914

II. Kuzmin A, Korhonen L, Kivinen S, Hurskainen P, Korpelainen P, Tanhuanpää T, Maltamo M, Vihervaara P, Kumpula T (2021) Detection of European Aspen (Populus tremula L.) Based on an Unmanned Aerial Vehicle Approach in Boreal Forests. Remote Sensing, 13(9), 1723. https://doi.org/10.3390/rs13091723

III. Hardenbol AA, Kuzmin A, Korhonen L, Korpelainen P, Kumpula T, Maltamo M, Kouki J (2021) Detection of aspen in conifer-dominated boreal forests with seasonal multispectral drone image point clouds. Silva Fennica, vol. 55 (4), 10515. https://doi.org/10.14214/sf.10515

IV. Kuzmin A, Korhonen L, Tanhuanpää T, Kukkonen M, Maltamo M, Kumpula T (2026) Classification of Tree Species and Standing Dead Trees in Boreal Forests Using UAV-Based RGB, Multispectral, and LiDAR point clouds. Remote Sensing in Ecology and Conservation. https://doi.org/10.1002/rse2.70070

Anton Kuzmin was the primary author of three articles (I, II and IV) and shared first authorship with Hardenbol in article III. The primary author conducted most of the data analyses, data preparations and implemented the required modelling routines. Writing of the manuscripts was carried out in collaboration with the co-authors.

TABLE OF CONTENT

LIST OF ABBREVIATIONS

3D	Three Dimensional
ALS	Airborne Laser Scanning
CHM	Canopy Height Model
DBH	Diameter at Breast Height
DTM	Digital Terrain Model
GCP	Ground Control Point
GLCM	Gray Level Co-occurrence Matrix
GNDVI	Green Normalized Difference Vegetation Index
GNSS	Global navigation satellite system
ITD	Individual tree detection
LDA	Linear Discriminant Analysis
LiDAR	Light Detection And Ranging
LOOCV	Leave-One-Out Cross-Validation
NDRE	Normalized Difference Red Edge Index
NDVI	Normalized Difference Vegetation Index
OBIA	Object-Based Image Analysis
PPC	Photogrammetric Point Cloud
RF	Random Forest
RFE	Recursive Feature Elimination
RTK	Real Time Kinematic
SfM	Structure from Motion
SVM	Support Vector Machine
TLS	Terrestrial Laser Scanning
VRS	Virtual Reference Station
UAV	Uncrewed Aerial Vehicle

INTRODUCTION

Boreal forests represent the largest terrestrial biome on Earth, spanning vast regions of the Northern Hemisphere including Canada, Russia, and Scandinavia (Kayes and Mallik, 2020). In Finland, boreal forests cover most of the country and are characterized by a relatively simple species composition dominated by coniferous species such as Scots pine (*Pinus sylvestris* L.*)* and Norway spruce (*Picea abies* (L.) Karst.), alongside broadleaved species like birches (*Betula pendula* Roth, *Betula pubescens* Ehrh.) and the ecologically significant European aspen (*Populus tremula* L.). These ecosystems play a critical role in global carbon cycling, climate regulation, and timber production, while also serving as habitats for a wide range of flora and fauna (Bradshaw et al., 2009).

Importance of tree species in forest management and biodiversity assessment

Understanding tree species composition is fundamental to both sustainable forest management and biodiversity conservation. Accurate species-level information supports forest planning, timber harvesting, habitat modeling, and conservation efforts, particularly in the face of climate change, which is reshaping forest ecosystems and challenging their resilience (Brockerhoff et al., 2017). Tree species composition is fundamental to quantitative forest inventories, as species-specific allometric models are needed to estimate biomass, volume, and wood density, thereby influencing carbon stock assessments, growth projections, and risk evaluations related to drought, windthrow, and pests (Vorster et al., 2020). Species-specific data are increasingly important for monitoring forest health, guiding adaptive management strategies, and supporting biodiversity assessments at local, regional, and global scales (Gaines et al. 1999). In boreal forests dominated by Scots pine and Norway spruce, broadleaved species such as European aspen play a significant ecological role by enhancing structural diversity and providing keystone resources for a wide range of organisms, including epiphytic lichens, saproxylic insects, and cavity-nesting birds. Large-diameter aspen trees (>20–25 cm) are especially valuable from a biodiversity perspective (Latva-Karjanmaa et al., 2007; Maltamo et al., 2015; Hyvärinen et al., 2019; Baroni et al., 2020; Kivinen et al., 2020; Toivonen et al., 2024). Despite its ecological importance, European aspen is often underrepresented in forest inventories due to its low economic value and patchy occurrence (Esseen et al. 1997; Kuuluvainen 2002). It is frequently grouped with other minor deciduous species in forest resource data, limiting species-specific insights (Packalen and Maltamo, 2007; Korpela et al., 2010). Traditional inventory methods, designed for more uniformly distributed and commercially valuable species, are not well suited for detecting scattered broadleaves like aspen (Kangas, 2006; Holmgren et al., 2008; Maltamo et al., 2015; Toivonen et al., 2023). Furthermore, historical forest management practices favoring coniferous monocultures and the absence of natural disturbances have reduced aspen abundance (Kivinen et al., 2020). In current airborne laser scanning (ALS) based forest management inventory systems, species-specific data are typically provided only for pine, spruce, and aggregated deciduous species, with aspen grouped into a broadleaf category - thus obscuring its presence in stand-level summaries (Maltamo et al., 2021). This generalization limits the detection and monitoring of aspen, despite its ecological significance in boreal forest ecosystems. Moving beyond aggregated stand-level summaries toward spatially explicit individual-tree information substantially improves the capacity to identify and monitor this species. When species are resolved at the individual-tree level and linked to precise spatial coordinates, inventories can identify rare or patchily distributed trees that would otherwise be masked in stand-level statistics. Such spatial explicitness also enables re-identification of the same trees over time, supporting long-term monitoring of ecologically valuable individuals.

In addition, deadwood elements, particularly standing dead trees, provide critical microhabitats and are widely recognized as key indicators of ecological continuity and biodiversity value (Martikainen et al., 2000; Kuuluvainen et al., 2017; Löfroth et al., 2023). Boreal forests, with their expansive reach and unique ecological characteristics, require detailed and accurate classification methods for effective management. Mixed-species forests that include such elements support greater species richness and a broader range of ecosystem services than monocultures (Carnol et al., 2014). Therefore, the ability to accurately identify and monitor tree species and deadwood components is essential for effective forest management, conservation planning, and long-term ecological sustainability in boreal landscapes. In this context, misclassification of tree species can propagate into biased biomass and carbon estimates (Vorster et al., 2020; Xing et al., 2019), distort biodiversity indicators, and reduced reliability of decision-support systems (Fassnacht et al., 2024). Improving species-level detection is thus not only an ecological objective but also a prerequisite for robust and management-relevant forest inventory systems. Such monitoring is also critical for detecting early signs of forest disturbances, including insect outbreaks like bark beetle infestations, which can rapidly alter forest structure and biodiversity dynamics (Seidl et al., 2017; Hlásny et al., 2021; Patacca et al., 2023).

Remote sensing technologies

Remote sensing has become a cornerstone of modern forest inventory and monitoring, offering spatially comprehensive and repeatable data for assessing forest structure, composition, and condition. Traditional airborne remote sensing platforms, such as crewed aircraft and satellites, have been widely applied in forest inventories and large-scale mapping, primarily through the use of multispectral imagery and airborne laser scanning (ALS) (Maltamo & Packalen, 2014; Næsset, 2014). These technologies have proven effective for estimating key forest attributes such as volume, biomass, canopy height, and land cover type, and continue to play a central role in national and regional forest monitoring programs (Ørka et al., 2013; Fassnacht et al., 2016). In parallel, Earth observation is increasingly used for biodiversity monitoring, offering spatial and temporal information on vegetation structure, phenology, and composition, supporting scalable assessments of ecosystem health and biodiversity patterns (Lausch et al., 2016; Skidmore et al., 2021; Berner & Goetz, 2022; Reddy et al., 2024).

In the Nordic countries, ALS-based forest inventory systems represent some of the most advanced operational implementations of remote sensing worldwide. Area-based approaches integrating ALS and aerial imagery are routinely used to produce stand-level estimates of volume, basal area, and dominant species with high accuracy (Maltamo et al., 2021). High-density ALS data have also further enabled individual tree detection (ITD) methods, supporting tree height estimation and crown delineation under favorable conditions (Vauhkonen et al., 2012). However, operational species classification at the individual-tree level remains challenging, particularly for sparsely distributed broadleaves and ecologically important but low-abundance species. Satellite imagery, while useful for broad-scale monitoring, often lacks the spatial resolution needed for individual tree-level analysis, particularly in heterogeneous or mixed-species stands (Helfenstein et al., 2022). Airborne laser scanning provides rich structural information, such as tree height, crown dimensions, and vertical canopy profiles, but lacks the spectral detail required for reliable species-level classification when used in isolation (Ørka et al., 2013; Vauhkonen et al., 2013; Michałowska & Rapiński, 2021). Similarly, passive optical sensors can deliver high-resolution spectral data but are challenged by dense canopy layers, variable lighting, and cloud cover, which are common in boreal environments with short growing seasons (Fassnacht et al., 2024).

Recent studies have demonstrated that combining structural and spectral data sources can significantly enhance classification outcomes (Viinikka et al., 2020; Mäyrä et al., 2021; Zhu et al., 2025). However, even with integrated approaches, accurately detecting sparsely distributed biodiversity indicators, such as standing dead trees and European aspen, remains a challenge due to their low abundance, irregular spatial patterns, and spectral similarity to other species (Petrou et al., 2015; Reddy, 2021). These gaps highlight the need for more flexible, ultra-high-resolution sensing approaches capable of supporting individual-tree-level species classification and targeted biodiversity assessments, such as those provided by Uncrewed Aerial Vehicles (UAV).

UAV-based approach

UAVs have become a powerful and increasingly accessible tool in forest remote sensing, offering a level of flexibility, spatial resolution, and repeatability that surpasses conventional platforms like satellites or crewed aircraft (Colomina and Molina, 2014; Puliti et al., 2015; Torresan et al., 2017; Guimaraes et al., 2020). UAVs can be rapidly deployed, operate under variable weather conditions, and fly at low altitudes to capture data at ultra-fine spatial resolution, enabling individual tree-level analysis even in structurally complex stands (Zhong et al., 2024; Fraser et al., 2025; Nevalainen et al., 2025). Their ability to carry RGB, multispectral, or LiDAR sensors allows for the collection of both spectral and structural information, supporting detailed species classification and structural assessments. These capabilities make UAVs particularly well-suited for detecting ecologically important but spatially sparse elements such as standing dead trees and broadleaved species like European aspen, which are often overlooked in coarser-scale datasets (Mäyrä et al., 2025).

Modern UAV systems support a diverse array of optical and active sensors, including RGB, multispectral, and LiDAR, enabling the collection of both spectral and structural information. Optical sensors are widely used to generate high-resolution orthomosaics and 3D point clouds through photogrammetric processing techniques such as Structure from Motion (SfM). Multispectral sensors expand this capacity by capturing reflectance across multiple wavelength bands, improving the ability to distinguish between tree species based on subtle differences in canopy reflectance. LiDAR-equipped UAVs, though more expensive, provide precise three-dimensional measurements of forest structure, which are particularly valuable for assessing canopy complexity and identifying structural indicators like standing dead trees. While combining spectral and structural data sources can enhance classification accuracy, the increased cost and operational complexity have led to continued research into whether simpler, single-sensor approaches can still meet the accuracy requirements of practical forest monitoring and biodiversity assessment (Kukkonen et al., 2019). RGB and multispectral imagery capture canopy reflectance characteristics, enabling species discrimination based on color, texture, and phenological differences. Under favorable conditions, spectral features alone can achieve high classification accuracies when species exhibit distinct reflectance signatures. In contrast, LiDAR provides three-dimensional structural information and the ability to penetrate the canopy, improving tree detection and delineation, particularly in dense or multilayered stands. However, structural features alone rarely provide sufficient separability for robust species-level classification, as architectural traits often overlap among species. Thus, LiDAR is most effective when combined with spectral information, with its principal advantage being improved tree detection and three-dimensional structural characterization.

Despite the increasing use of UAVs in forest applications, key research gaps persist, particularly in biodiversity-focused assessments. Although European aspen has been included in previous UAV-based classification studies (Saarinen et al. 2018; Tuominen et al. 2018; Franklin & Ahmed, 2018), it has typically been represented by relatively small sample sizes or evaluated outside sparse conifer-dominated boreal stand conditions. In many cases, the number of aspen observations was substantially lower than that of dominant coniferous species, which contributed to reduced classification accuracy for aspen compared to Scots pine and Norway spruce. For, example, Tuominen et al. (2018) included 19 aspen trees out of 673 total samples in an arboretum, while Franklin and Ahmed (2018) reported high classification accuracy for quaking aspen (*Populus tremuloides*) in a Canadian hardwood forest but based independent validation on only five aspen crowns. Together these findings indicate that systematic evaluation of European aspen under mixed, boreal forest conditions has remained limited. In parallel, explicit identification of standing dead trees as a separate class has received comparatively less attention in UAV-based studies (Amiri et al., 2019; Polewski et al., 2019). Only a few studies have attempted to classify both European aspen and standing dead trees within the same UAV-based framework, despite their complementary value as biodiversity indicators in boreal forests. Recent advances highlight the promise of UAV technology in this area. Multispectral and LiDAR data from UAVs have been used to classify tree species with high accuracy, while RGB imagery combined with deep learning approaches has proven effective for species-level mapping (Li et al., 2024; Huang et al., 2024). These developments underscore UAVs' growing role in fine-scale ecological monitoring and their potential to support species-specific biodiversity assessments in structurally diverse forest environments.

Objectives

The main objective of this dissertation was to evaluate how effectively UAV-based remote sensing methods can be used to classify tree species composition in boreal forests. In more detail, the objectives are:

i. Identify which UAV-derived features: spectral, structural, shape, texture-based, or their combination, contribute most to accurate classification of boreal tree species (I, II, III, IV).
ii. Assess how seasonal conditions, including winter snow cover, leaf-off, leaf-flush, and leaf-on periods, affect the accuracy of UAV-based tree species classification (I, III).
iii. Determine which UAV sensor configurations (RGB, multispectral, LiDAR, or their combinations) provide the highest accuracy for detecting selected key biodiversity

indicators, particularly European aspen and standing dead trees, in mixed boreal forests (II, III, IV).

MATERIALS

Study areas

Three boreal forest study sites were used in this thesis, hereafter referred to as Sodankylä (Study **I**), Evo (Study **II** & **IV**) and Lieksa (Study **III**) (Figure 1). Sodankylä is located in the northern boreal forest region of Lapland, Northern Finland, whereas Evo is situated in Hämeenlinna in Southern Finland, and Lieksa is located in the region of North Karelia, Eastern Finland. The main tree species across all study areas include Scots pine (*Pinus sylvestris* L.), hereafter referred to as pine, Norway spruce (*Picea abies* (L.) Karst.), hereafter referred to as spruce, and broadleaved species, primarily downy birch (*Betula pubescens* Ehrh.) and silver birch (*Betula pendula* Roth), hereafter referred to as birch. Additionally, European aspen (*Populus tremula* L.), hereafter referred to as aspen, although less abundant, represents an ecologically significant component of forest composition in Evo and Lieksa study areas. Sodankylä is characterized by low-density, mixed coniferous forests and open peatlands, while Evo and Lieksa encompass mixed stands with mature and old-growth forest patches, often featuring scattered occurrences of aspen and standing dead trees. Forests in Evo and Lieksa include both managed and protected forest stands. Timber production remains a primary management goal in managed areas, whereas protected areas emphasize biodiversity conservation and preservation of old-growth forest characteristics. In contrast, the Sodankylä study area includes predominantly managed forests, with timber production as the primary forest management objective.

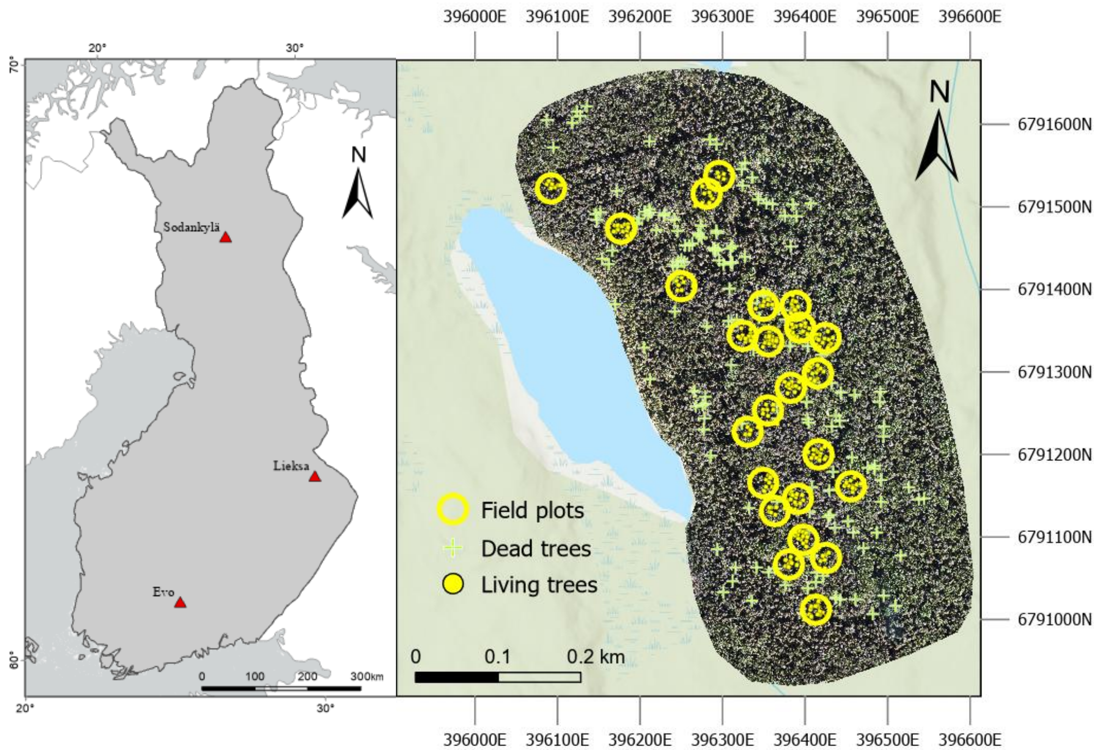

Figure 1. Locations of the study areas (left). Example of one site with individually mapped living and dead trees and field plots in Evo (right)

Field data

Three separate tree-wise field campaigns were conducted to collect reference data used in Study **II**, **III** and **IV** in Evo and Lieksa study areas. These campaigns involved extensive inventories in which individual tree species (Scots pine, Norway spruce, birches and European aspen), locations and diameters at breast height (DBH) were recorded. Additionally, standing dead trees were measured in Evo to support biodiversity-related analyses (study **IV**). In contrast, for the Sodankylä study area (study **I**), no field reference data were collected; instead, tree species were identified using careful visual interpretation of high-resolution helicopter-based RGB images (Table I).

Table 1 Summary of reference data collected for this thesis. Species marked with (*) were identified through visual interpretation.

	Study I	Study II	Study III	Study IV
Location	Sodankylä	Evo	Lieksa	Evo
Number of measured trees	1134	771	510	1205
Species	Spruce*, Pine*, Birch*	Spruce, Pine, Birch, Aspen	Spruce*, Pine*, Birch, Aspen	Spruce, Pine, Birch, Aspen, Standing dead trees

In Evo, field reference data were collected during two separate campaigns. The first campaign (study **II**), took place in July 2018 and involved 25 circular field plots with a radius of 9 m (approximately 254 m^2 each), located in semi-closed and closed-canopy forests. Within these plots, individual tree species, locations, heights, and DBH were recorded for trees clearly visible from UAV imagery. Due to the sparse distribution of European aspen, additional measurements of individual aspen trees were conducted outside the plots to ensure sufficient representation. The second campaign (study **IV**) took place in June and autumn of 2021. A total of 80 circular plots (radius 9 m, approximately 254 m^2 each) were established in mature forest stands and younger stands. Individual trees representing Scots pine, Norway spruce, birches (downy and silver birch merged), European aspen, and standing dead trees were measured, with species, positions, and DBH recorded. Similar to the previous campaign, supplementary measurements outside plot boundaries were carried out during autumn 2021, specifically targeting European aspen and standing dead trees to ensure representative sampling. Precise tree locations in both campaigns were recorded using Trimble R10 RTK-GPS.

In Lieksa (study **III**), field data were collected in 2019 within three old-growth forest stands. The inventory primarily targeted European aspen and nearby birches, recording species, locations, and DBH. Tree positions were initially measured with GNSS (Topcon HiPer V and Trimble R10) and subsequently verified using UAV-based RGB imagery. Additional reference trees of Scots pine and Norway spruce were identified and verified visually from aerial images, without DBH measurements.

Remotely sensed data

Helicopter-based imagery

Helicopter-based RGB images were acquired during the SNORTEX campaign on March 19, 2010, over the Sodankylä study area (Roujean et al., 2010; Manninen and Roujean, 2014). A Canon Powershot A640 camera with a 0.7× wide-angle lens (WC-D58N) was mounted vertically on the helicopter landing gear (Manninen et al., 2009). Images were captured every three seconds, with GPS coordinates recorded for each image. A total of 37 low-altitude images (27–71 m above ground) were selected from the flight, providing spatial resolutions between 0.8 and 2.1 cm per pixel (Figure 2). Images were stored directly as standard JPG files without photogrammetric calibration. Weather conditions were suboptimal due to sunlight causing distinct shadows on the snow-covered ground.

Figure 2. Example of the image taken from the helicopter in study I.

UAV-based data

UAV-based aerial imagery was collected using different platforms and sensor configurations, varying across Studies II–IV (Figure 3). In study **II** and **III**, UAV-based imagery was collected using multiple UAV platforms. For RGB data, a fixed-wing eBee Plus RTK equipped with a SenseFly S.O.D.A. (**II**) and a DJI Phantom 4 RTK (**II**, **III**) with its integrated high-resolution RGB camera were used. Multispectral imagery was collected using an eBee Plus RTK carrying a Parrot Sequoia sensor (**II**) and a DJI Matrice 210 equipped with a MicaSense RedEdge-M sensor (**II** and **III**). In study III, images were acquired across five separate dates spanning different seasonal and phenological phases (leaf-off, leaf-flush, leaf-on, and autumn senescence periods). In study **IV**, UAV imagery was simultaneously collected using a DJI Matrice 300 RTK equipped with a DJI Zenmuse P1 RGB camera and a MicaSense RedEdge-MX multispectral sensor. Additionally, UAV LiDAR data were acquired using the same DJI Matrice 300 RTK platform equipped with a YellowScan Mapper+ laser scanner integrated with an Applanix APX-15 inertial measurement unit. Detailed information regarding flight parameters, sensor specifications, and acquisition settings for each study is provided in Table 2.

Figure 3. UAV platforms used in this thesis: DJI Phantom 4 RTK, Sensefly eBee plus and DJI Matrice 210 (all left), DJI Matrice 300 RTK (right).

Table 2 Overview of UAV platforms, sensor configurations, and acquisition parameters in studies II–IV.

Study	Platform + Sensor setup	Altitude, m	Side/front overlap, %	GSD, cm
II	eBee Plus RTK + SenseFly S.O.D.A. RGB DJI Phantom 4 RTK + Integrated RGB camera eBee Plus RTK + Parrot Sequoia DJI Matrice 210 + MicaSense RedEdge-M	130–150	85/85	3.9–4.9
III	DJI Matrice 210 + MicaSense RedEdge-M	135	80-85/ 75-85	9
	DJI Phantom 4 RTK + Integrated RGB camera	140	85/85	3.8
IV	DJI Matrice 300 RTK + Zenmuse P1 & RedEdge-MX	120	85/85	RGB: 1.4–1.5 MSP: 4.2–5.0
	DJI Matrice 300 RTK + YellowScan Mapper+ LiDAR	80–100	50	LiDAR: 300–700

Across all UAV RGB flights (**II**, **III** and **IV**), precise positioning corrections were achieved using Virtual Reference Station (VRS) RTK signals, ensuring high geometric accuracy. For multispectral imagery, artificial ground control points (GCPs) extracted from accurately georeferenced RGB mosaics were used to align multispectral data in studies **II** and **IV**. In contrast, for study **III**, physical ground control points were installed across the study sites to accurately georeference multispectral imagery. Additionally, for all multispectral flights (**II–IV**), radiometric calibration was consistently performed before and after each flight using reflectance calibration targets to ensure accurate spectral data quality and comparability.

METHODS

Point cloud and mosaic generation

Photogrammetric point clouds (PPCs) were generated from RGB and multispectral UAV imagery using the Structure-from-Motion (SfM) technique implemented in Agisoft Metashape software (Agisoft LLC, St. Petersburg, Russia). Across all studies (**II**, **III**, **IV**), the standard workflow began with aligning UAV images based on image overlap and sensor geometry, deriving initial camera positions and orientations. Subsequently, dense point clouds were computed at high-quality settings, incorporating mild depth filtering to optimize detail while minimizing noise and outliers. Figure 4 illustrates the general workflow applied in studies **II**, **III**, and **IV**, highlighting the main steps.

For RGB imagery (studies **II**, **III** and **IV**), PPCs were produced with very high spatial resolutions (typically <5 cm), supporting accurate individual tree delineation. Multispectral imagery-derived PPCs (studies **III**, and **IV**) offered spectral information in addition to structural data, enabling detailed tree-species-specific analyses. For study **IV**, LiDAR point clouds acquired with the YellowScan Mapper+ sensor were processed independently, using CloudStation software for accurate strip alignment, classification of ground points and export in laz format.

All resulting point clouds were normalized to terrain level using available digital terrain models (DTMs) from airborne laser scanning data provided by the National Land Survey of Finland. In study **IV**, the LiDAR-derived point cloud was normalized using a terrain model derived from the LiDAR data itself. The resulting normalized point clouds served as primary data inputs for subsequent individual tree detection, crown segmentation, feature extraction, and classification analyses.

In study II, multispectral UAV images collected were processed into georeferenced multispectral orthomosaics using Agisoft Metashape software for further feature extraction. In studies **II**, **III** and **IV**, RGB orthomosaics generated from UAV imagery primarily served as visual reference layers to validate and assess the quality of individual tree detection and crown segmentation results.

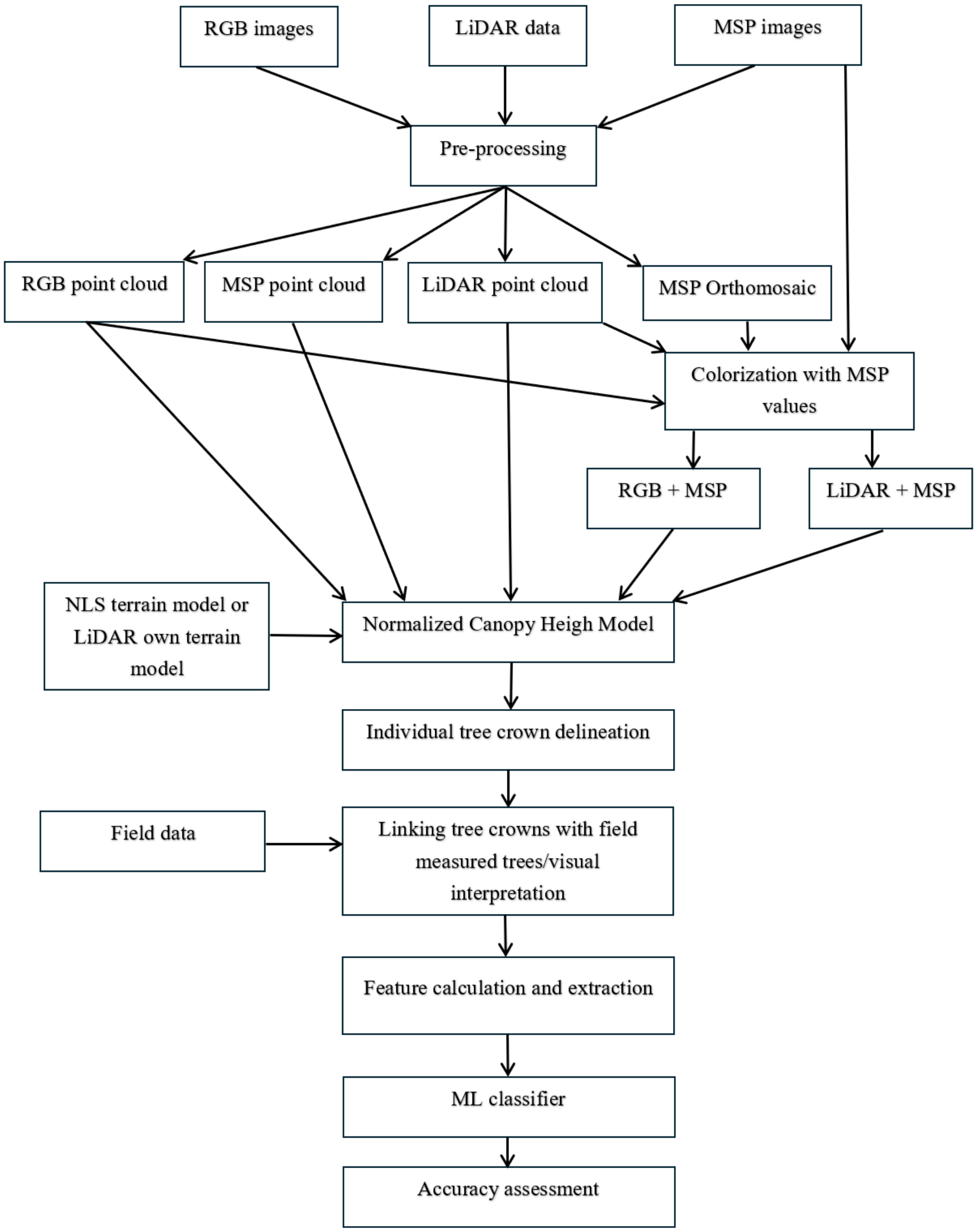

Figure 4. General workflow for processing UAV-based data in Studies II, III and IV.

Individual tree detection and crown segmentation

In study **I**, individual tree crown segmentation was performed using object-based image analysis (OBIA) approach directly applied to pre-selected high-resolution helicopter-based RGB imagery using eCognition software (Trimble, Munich, Germany). The process started by masking out the snow-covered background through a brightness-based threshold, effectively separating tree crowns from shadows and ground. The tree-crown segments were then delineated using multiresolution segmentation algorithm, grouping spectrally and texturally similar neighboring pixels into homogenous crown-level objects.

In studies **II** and **IV**, individual tree detection and crown segmentation were performed using an automated approach based on UAV-derived point clouds. The point clouds were height-normalized using digital terrain models (DTMs) to represent canopy height above ground level. Canopy height models (CHMs) were generated and crowns boundaries delineated using a watershed segmentation algorithm implemented in LAStools (LAStools, 2025) and R (R Core Team 2025). A minimum height threshold of 2 m was applied to exclude ground and low vegetation. However, no explicit pixel-level background masking (e.g., spectral thresholding of shadow or non-canopy pixels) was applied after segmentation, meaning that some crown polygons may still contain background or neighboring canopy elements. Segmentation accuracy was visually evaluated against high-resolution RGB orthomosaics.

In study **III**, both automatic and manual segmentation approaches were explored. Automatic crown delineation based on watershed segmentation was tested but resulted in lower accuracy compared to manually delineated crowns. To provide best-case reference and to isolate seasonal effects from segmentation errors, manual crown delineation based on RGB orthomosaics and CHMs was therefore used for model development and accuracy assessments.

Feature extraction

In study **I**, features were extracted at the segment level directly from RGB imagery using eCognition software. Spectral features included mean and standard deviation values of the RGB bands and brightness. Texture features were derived using Gray-Level Co-occurrence Matrix (GLCM) metrics such as contrast, homogeneity, entropy, and correlation to describe texture variation within each crown. Additionally, shape features, including crown length, width, area, and roundness were calculated to describe form and compactness of image segments and support object-based species classification.

In study **II**, crown segments delineated from RGB point clouds were overlaid onto multispectral orthomosaics to extract spectral features. Mean and standard deviation values of each multispectral band (Green, Red, Red Edge, and Near-Infrared) were calculated within each segmented crown polygon. Additionally, mean and standard deviation of spectral values from the RGB bands were extracted for each crown segment, providing complementary spectral information for species classification. Because crown segmentation was derived from RGB-based point clouds while spectral features were extracted from multispectral mosaics that were georeferenced using natural object–based control points from the RGB orthomosaic (≈2 cm horizontal accuracy), minor residual spatial misalignments between datasets may still have occurred, potentially causing some crown segments to include background or neighboring canopy pixels.

In studies **III** and **IV**, spectral and structural features were extracted directly from both RGB and multispectral PPCs for each delineated tree crown segment. Only points ≥ 2 m above ground were included to reduce ground contamination. Spectral features consisted of the mean and standard deviation were derived from reflectance values in the visible (Blue, Green, Red), Red-Edge, and near-infrared wavelengths, while structural features included metrics described crown height distribution, crown shape, and canopy density derived from 3D point cloud geometry.

In studies **II**, **III**, and **IV**, all spectral reflectance values were normalized using the brightness-based method proposed by Yu et al. (1999). This involved dividing each band's reflectance by the sum of all bands for the same point, effectively reducing illumination variability and improving consistency across crown-level spectral features. Additionally, vegetation indices were calculated to enhance species differentiation. In study **III**, the Normalized Difference Vegetation Index (NDVI) and the Green Normalized Difference Vegetation Index (GNDVI) were computed, while study **IV** included NDVI and the Normalized Difference Red Edge Index (NDRE). For each index, statistics such as mean, maximum, and 95th percentile were extracted per tree crown segment.

In study **IV**, two categories of predictor variables were extracted from the LiDAR data for each segmented tree: intensity and texture features. Intensity features were computed at the voxel level by dividing the point cloud into a 3D grid centered on the treetop, assigning each voxel the average return intensity of all echoes within it. The voxel grid had a consistent number of voxels per tree, though voxel dimensions varied by tree size. Texture features (angular second moment, contrast, correlation, and sum average) were derived from horizontal cross-sections of the point cloud using binary raster slices (Haralick et al. 2007). Only first and single LiDAR echoes above 50% of the tree height were used to minimize understory effects. In total, 160 LiDAR features were computed. For further methodological details, see Kukkonen et al. (2024).

Classification algorithms

Three different classification algorithms were used across the studies, depending on data complexity, number of features, and classification objectives. Each algorithm was applied independently within a given study, and species classification performance was evaluated using standard accuracy metrics.

Linear discriminant analysis

In studies **I** and **III**, a Linear Discriminant Analysis (LDA) was used as the classification method. LDA was selected for its simplicity and ability to handle relatively low-dimensional feature sets. In Study **I**, LDA was applied to segment-level RGB spectral, texture, and shape features extracted from high-resolution winter imagery. In study **III**, LDA was used to classify tree species based on both multispectral and structural features derived from UAV point clouds and vegetation indices. The objective of LDA is to find a linear combination of features that primarily characterize or separate two or more classes from one another (Hastie et al. 2009).

Support vector machine

In study **II**, a Support Vector Machine (SVM) with a radial basis function kernel was used to classify tree species based on RGB and multispectral spectral features. SVM was chosen due to its effectiveness in handling non-linearly separable classes and relatively small, high-dimensional datasets. The classifier was trained using crown-level features extracted from both RGB and multispectral imagery, and performance was evaluated using cross-validation with balanced class representation.

Random Forest

In study **IV**, tree species and standing dead trees were classified using the Random Forest algorithm. This method was chosen for its robustness in managing multicollinearity, capturing non-linear relationships, and handling high-dimensional datasets without a need for prior feature selection (Fox et al., 2017; Cosenza et al. 2021). The diverse feature set used for classification included spectral, structural, and LiDAR-derived variables. The model was trained using reference data for the major boreal tree species and deadwood classes, and variable importance metrics were calculated to assess the relative contribution of each feature type to the overall classification performance.

Performance assessment

The performance of the methodology used in studies **I** and **III** was evaluated using confusion matrices and standard classification accuracy metrics, including overall accuracy (OA), user's accuracy (UA), producer's accuracy (PA), and Cohen's kappa coefficient. Both studies applied leave-one-out cross-validation (LOOCV), though the strategy differed slightly in implementation. In study **I**, a leave-image-out approach was used: for each iteration, all segments from one image were excluded, the model was trained on the remaining data, and predictions were made for the omitted image segments. This process was repeated across all images to ensure generalizability across varying imagery conditions. In study **III**, LOOCV was conducted at the individual crown level, with each tree segment left out once and predicted using a model trained on all remaining data. Additionally, study **III** incorporated a simulated annealing-based feature selection loop, with final predictions averaged across 100 iterations to reduce variability introduced by the selection process.

In study **II**, classification performance was assessed using a two-stage process involving recursive feature elimination (RFE) and independent hold-out testing. First, RFE was applied to the full dataset using 10-fold cross-validation as an outer resampling method to identify the most relevant predictors and reduce model overfitting. This procedure was repeated 21 times to account for the stochastic nature of the algorithm, and the final number of features was selected based on the median overall accuracy. After feature selection, the dataset was partitioned into 70% training and 30% testing subsets using stratified random sampling. The model was trained on the training data and evaluated on the test set, with classification accuracy reported using OA, UA, and PA derived from confusion matrices.

In study **IV**, the dataset was divided using proportional stratified random sampling into 70% training and 30% testing subsets. The training data were used to build the model, while the hold-out test set served for independent validation and calculation of accuracy metrics. Classification performance was evaluated using confusion matrices, Cohen's kappa, and the F1-score, which represents the harmonic mean of user's (UA) and producer's accuracy (PA). In addition to accuracy metrics, feature importance scores were computed to assess the relative contribution of variables from RGB, multispectral, and LiDAR-derived point clouds.

RESULTS

This chapter presents the main findings from studies I–IV, which examined the potential of UAV-based remote sensing methods for tree species classification and biodiversity assessment in boreal forests. The results are organized around key research themes, including overall classification accuracy, comparisons between still-image and point cloud approaches, feature importance, and the detection of ecologically significant elements such as European aspen and standing dead trees.

Overall tree species classification performance

The classification performance of UAV-based remote sensing methods was evaluated across studies **I–IV** using varying data sources, sensor configurations, segmentation strategies and classification algorithms. The aim was to assess how effectively different combinations of spectral and structural features, as well as machine learning techniques, could distinguish between dominant boreal tree species. The results showed consistently high classification accuracy across all studies, with particularly strong performance in setups that integrated multispectral and structural information. A summary of the classification methods, data types used, overall accuracy, kappa statistics, and target species is provided in Table 3.

The classification results presented in Table 3 highlight the effectiveness of various UAV-based remote sensing approaches for tree species identification in boreal forests. Across all studies, overall accuracy ranged from 79% to 95%, indicating a consistently strong performance regardless of platform or classification method. Kappa values between 0.70 and 0.93 further support the reliability of the classification outcomes, showing substantial agreement between predictions and reference data in all cases. The highest classification accuracy was achieved in study III, where PPCs derived from RGB and multispectral imagery were used for both manual and automatic crown delineation and spectral feature extraction. The use of manual crown delineation and early-season imagery contributed to an overall accuracy of 95% and a kappa of 0.93, emphasizing the value of precise segmentation, particularly in identifying scattered broadleaved species, like aspen. However, even with automatic segmentation, the study achieved great results (OA = 92%, Kappa = 0.90), highlighting the benefit of precise segmentation and optimal phenological timing.

Table 3 Summary of data sources, classification methods, accuracy metrics, and target species in Studies I–IV. OA denotes overall accuracy, LDA denotes linear discriminant analysis, SVM denotes support vector machine and RF denotes random forest.

Study	Data used	Classification method	OA (%)	Kappa	Classes
I	RGB	LDA	84	0.78	Pine, Spruce, Birch
II	RGB+MSP	SVM	83	0.76	Pine, Spruce, Birch, Aspen
III	RGB+MSP (automatic ITD)	LDA	92	0.90	Pine, Spruce, Birch, Aspen
	RGB+MSP (manual ITD)	LDA	95	0.93	Pine, Spruce, Birch, Aspen
IV	LiDAR+MSP	RF	79	0.70	Pine, Spruce, Birch, Aspen, deadwood

Study **II** used RGB-derived PPCs for crown segmentation and multispectral imagery for spectral feature extraction from multiple UAV platforms, achieved a similar high accuracy of 83% (kappa 0.76). In this case, mosaic-based spectral features were combined with tree delineations derived from RGB point clouds, offering a hybrid approach that was particularly effective for binary classification involving European aspen.

The lowest overall accuracy (79%) was reported in study **IV**, where a combination of LiDAR and multispectral data was used alongside a Random Forest classifier. While the structural richness of LiDAR added value, especially for detecting standing dead trees, it also introduced classification complexity, as this study included an additional class (deadwood). The slightly lower kappa (0.70) reflects this broader classification scope and the associated challenge of distinguishing five target classes. These findings collectively underscore that combining spectral and structural features, especially when paired with high-quality segmentation, yields the most reliable species classification outcomes in boreal forests.

Point cloud Vs. image-based classification

The results summarized in Table 3 enable a comparison between image-based and point cloud–based classification approaches applied across the four studies. Studies **I** and **II** relied primarily on 2D image features, while studies **III** and **IV** leveraged UAV-derived 3D point clouds, either from photogrammetry or LiDAR, for both segmentation and feature extraction. This comparison highlights the role of spatial structure, segmentation method, and data dimensionality in influencing classification accuracy.

In Study **I**, which relied on helicopter-based RGB imagery and object-based segmentation, the model achieved a solid overall accuracy of 84% and a kappa coefficient of 0.78, confirming that shape, texture, and spectral features alone can yield robust results, particularly under winter conditions with high contrast between tree crowns and background snow. However, the absence of 3D structural information limited the detection of vertical canopy complexity and finer crown separation.

Study **II** implemented a hybrid approach in which RGB and multispectral imagery were used for feature extraction, while point cloud data (from RGB photogrammetry) supported crown segmentation. This combination led to a higher overall accuracy of 83% and kappa of 0.76, suggesting that even when structural data are not used directly for classification, their contribution to tree delineation can significantly enhance results.

A more advanced use of point clouds was implemented in studies **III** and **IV**, where both segmentation and classification were based on RGB- and multispectral-derived 3D point clouds. Study **III** achieved the highest classification performance overall, with manual segmentation yielding 95% accuracy and automatic segmentation reaching 92%. These results underscore the effectiveness of high-resolution point clouds in supporting precise crown delineation and robust classification, particularly when paired with early-season imagery. Among automatic approaches, RGB-derived segmentation outperformed multispectral-derived segmentation, highlighting the importance of dense, well-structured point cloud data.

Study **IV**, incorporating LiDAR-derived structural features, extended the classification to include standing dead trees. Although the overall accuracy was slightly lower at 79%, the study confirmed the utility of LiDAR in detecting structural indicators relevant to biodiversity monitoring.

Overall, the findings show that point cloud–based methods, especially when combined with well-timed spectral data and high-quality segmentation, offer superior classification performance. Image-based approaches remain useful, particularly when supported by high-resolution textures and favorable acquisition conditions. The most effective strategies, as demonstrated in Study **III** and **IV**, involve combining structural and spectral inputs—especially when collected simultaneously—to leverage the strengths of both data types.

Feature importance across data types

Understanding which features contribute most to accurate tree species classification is crucial for developing efficient and generalizable remote sensing workflows. Across the four studies, different types of features—spectral, structural, texture, and shape - were evaluated for their relative importance using a range of classification methods and sensor combinations.

In study **I**, where high-resolution RGB imagery from a helicopter was used under snow-covered winter conditions, classification was based on a combination of spectral, texture, and shape features extracted at the segment level. While no 3D structural data were available, the inclusion of GLCM-based texture metrics (e.g., contrast, entropy) and shape descriptors (e.g., crown area, roundness) enhanced the ability to differentiate between coniferous and broadleaved species. Although a formal ranking of feature importance was not performed, the successful classification outcome (84% OA) demonstrated the value of incorporating object-level geometry and texture in RGB-only imagery.

In study **II**, feature importance was formally assessed using recursive feature elimination (RFE) combined with SVM classification. Features were derived from both RGB and multispectral mosaics, with the latter proving more informative overall. Among the multispectral variables, those associated with red edge and near-infrared bands were consistently ranked highest. These features were particularly valuable for distinguishing European aspen, which exhibits subtle spectral differences from coniferous species. Visible-band spectral features, while contributing to the combined model, were generally less influential than multispectral ones.

Study **III** explored seasonal variation using multispectral photogrammetric point clouds, from which both spectral indices and structural features were extracted. The most important variables for species classification were NDVI and GNDVI, along with their statistical derivatives (mean and 95th percentile) computed per tree crown. These indices, particularly when captured during early phenological stages, contributed significantly to model accuracy. In contrast, structural features derived from point clouds were less influential in this study, likely due to the relatively similar height profiles among the species considered and the limited structural resolution of SfM point clouds.

In study **IV**, the integration of LiDAR-derived structural features with multispectral and visible-band spectral data provided a more comprehensive feature set for classification. Feature importance was evaluated using Random Forest variable importance metrics after simulated annealing-based feature selection. However, the most critical variables were entirely derived from multispectral indices and percentile-based reflectance values, with no structural LiDAR-based metrics appearing among the highest-ranked variables. Spectral features, particularly those derived from NDVI and NDRE indices, played a dominant role in the classification, especially for identifying aspen and standing dead trees. Visible-band spectral features had a relatively minor role compared to multispectral data, reflecting the added value of spectral diversity.

Across all studies, the most informative predictors consistently captured spectral variation in the red-edge and near-infrared regions, especially for distinguishing broadleaved species. Although LiDAR-derived structural variables were not among the highest-ranked classification predictors, the LiDAR sensor provided the most reliable individual tree detection and crown delineation performance. This improved segmentation quality formed a critical foundation for robust species classification. These insights support the continued development of multi-sensor classification approaches that leverage both spectral richness and detailed canopy structure for improved species mapping in boreal forests.

Biodiversity indicator assessment: European aspen and standing dead trees

Classification performance for European aspen was evaluated in studies **II–IV**, with results varying depending on segmentation methods, feature sets, and sensor combinations (Table 4). Study **III** achieved the highest accuracy for aspen, with a user's accuracy (UA) of 97%, producer's accuracy (PA) of 96%, and an F1-score of 97%, using manually delineated tree crowns and early-season multispectral imagery. Even with automatic segmentation, high accuracies were maintained - particularly with RGB-based point clouds (UA 85-97%, PA 79-93%) - highlighting the benefits of accurate crown delineation and phenological timing.

In study **II**, UAV-derived RGB and multispectral imagery were combined with SVM classification and recursive feature elimination. Aspen classification yielded UA of 88%, PA of 86%, and an F1-score of 87%. Multispectral features, especially those derived from red-edge and NIR bands, were most influential, while visible-band spectral features contributed less but improved results when used in combination.

Study **IV** integrated RGB, multispectral, and LiDAR data using a Random Forest model. Aspen classification reached UA of 84%, PA of 81%, and an F1-score of 82%, demonstrating reliable performance despite a more complex classification scenario involving additional classes and structural variation. The simultaneous collection of RGB and MSP data helped ensure strong alignment and effective feature integration.

In addition to aspen, standing dead trees were classified in study IV as a separate target class. LiDAR-derived structural features - such as vertical profiles, reduced canopy height, and point cloud gaps - played a critical role in distinguishing snags from live trees. While classification accuracy for deadwood was lower than for live species, the model successfully demonstrated the potential of UAV-LiDAR integration for fine-scale deadwood mapping, offering promising applications for biodiversity monitoring.

Table 4. Summary of classification accuracy for European aspen across studies II–IV, UA denotes User's accuracy, PA denotes Producer's Accuracy, LDA denotes linear discriminant analysis, SVM denotes support vector machine and RF denotes random forest.

Study	Data used	Classification method	F1-score, %	UA, %	PA, %
II	RGB+MSP	SVM	86	88	86
III	RGB+MSP	LDA	97	97	96
IV	LiDAR+MSP	RF	78	84	81

DISCUSSION

This thesis demonstrated that UAV-based remote sensing can effectively classify tree species and support biodiversity assessment in boreal forests. Across the four studies, different sensor configurations and classification approaches were evaluated to map tree species composition and key biodiversity indicators, specifically European aspen and standing dead trees. The overall classification accuracy ranged from 78% to 95%, with the highest performance achieved using manual segmentation and early-season multispectral data (study III). The results also showed that UAV-derived features, particularly when combining spectral and structural data, can provide sufficient accuracy for ecological applications, including the detection of sparsely distributed species like European aspen. Methodologically, the research employed both manual and automatic crown segmentation, revealing clear advantages in segmentation quality for manually delineated crowns, particularly in complex canopies. However, automatic approaches based on watershed segmentation of CHMs provided sufficient quality when supported by high-resolution point clouds. Feature extraction strategies varied across studies, with combinations of spectral, structural, and texture features yielding the most robust results. The use of multiple classification algorithms: LDA, SVM, and RF allowed for cross-comparison of modelling approaches. It is important to note that direct quantitative comparison across the studies is constrained by differences in study areas, forest structure, sensor configurations, ground sampling distance, and classification algorithms. Study I was conducted in Sodankylä, Study III in Lieksa, and Studies II and IV in Evo, each representing different stand conditions and acquisition settings. Therefore, cross-study comparisons should be interpreted as providing general methodological insights rather than strict experimental benchmarking under identical conditions. Where studies share similar settings (e.g., Studies II and IV conducted in Evo), comparisons are more directly informative but still influenced by differences in data processing and modelling choices.

The research highlights the feasibility of UAV-based species mapping in complex forest environments, providing a strong foundation for biodiversity-focused forest monitoring. Individual Tree Detection played a central role in the species classification pipeline, with crown segmentation forming the basis for associating spectral and structural features to individual trees. Studies **II**, **III**, and **IV** demonstrated that both RGB-derived and LiDAR-derived point clouds are viable for ITD, although segmentation quality remains a limiting factor. Manual segmentation outperformed automatic methods in terms of crown delineation and ultimately classification accuracy, especially in dense or overlapping canopies.

Recent progress in deep learning has expanded methodological options for tree species classification, with neural network architectures increasingly applied to multispectral, RGB, and LiDAR data (Nezami et al., 2020; Onishi & Ise, 2021; Mäyrä et al., 2021; Paheding et al., 2024). These approaches are capable of modelling complex spatial–spectral patterns and have demonstrated strong performance in structurally diverse forest environments. Compared with such studies (Fan et al., 2023; Zhang et al., 2025; Mäyrä et al., 2025), the accuracies achieved in this thesis were slightly lower, but the methodological context differs substantially. Deep learning models typically require large, well-annotated training datasets and considerable computational resources, which remain limiting factors in boreal forest applications, particularly for rare or ecologically important classes such as European aspen and standing dead trees. The growing availability of benchmark datasets (e.g., Mosig et al., 2024; Puliti et al., 2025) will likely reduce these constraints and enable more systematic comparisons in future research. Under current data conditions, however, the results of this thesis demonstrate that classical ITD-based segmentation combined with machine learning remains a robust and operationally feasible approach in boreal environments, especially where labeled data are limited (Lee et al., 2025).

The comparison of RGB, multispectral, and LiDAR sensors revealed that while each data type offers distinct strengths, their combination consistently led to improved classification performance. Multispectral data were particularly effective in capturing species-level spectral variation, while LiDAR provided detailed structural information crucial for identifying deadwood and supporting tree delineation. Very high spatially resolution RGB data, although more limited spectrally, contributed to improved segmentation when used to generate dense point clouds. However, the relatively low classification performance observed for RGB-only setups should be interpreted with caution. While texture metrics were included in the feature sets, their construction was not optimized or systematically evaluated. Texture features are known to be critical in RGB-based species classification, as highlighted in Study I and previous literature, yet the lack of standardized texture feature construction may have underrepresented their true potential within the RGB-based classification scenarios evaluated in this thesis. Future work should explore more advanced or multi-scale texture extraction methods to fully leverage the spatial detail of RGB imagery. Still, under favorable conditions, RGB and MSP single-sensor approaches proved valuable for cost-efficient biodiversity monitoring. Notably, single-sensor setups, especially those based on RGB or MSP, still produced reliable results under optimal conditions, highlighting their value for cost-efficient biodiversity monitoring.

Recent developments in hyperspectral UAV sensors provide another promising direction for improving tree species classification (Zhang et al. 2025). Unlike multispectral systems that capture a limited number of discrete spectral bands, hyperspectral sensors acquire reflectance data across hundreds of contiguous wavelengths, enabling the identification of subtle spectral variations between tree species. This level of spectral granularity is especially valuable when distinguishing morphologically similar or closely related species, or detecting early signs of physiological stress. Prior research has demonstrated the utility of UAV-based hyperspectral data in forest mapping. (Sothe et al. 2019; Zhong et al. 2022; Ma et al. 2024) For instance, Tuominen et al. (2018) achieved high overall classification accuracy across 26 species in a Finnish arboretum using hyperspectral and 3D features, although performance for minority classes such as European aspen was influenced by limited sample representation. Similarly, Saarinen et al. (2018) showed that dominant species were predicted more reliably than sparsely occurring deciduous species, highlighting the sensitivity of hyperspectral classification to class imbalance.Although hyperspectral UAV systems are still associated with high acquisition costs, limited spatial coverage, and computationally intensive data processing, they present substantial benefits for fine-scale biodiversity monitoring. In particular, their application could greatly improve the detection of rare or spectrally similar species and facilitate early identification of disease or environmental stress. As technology matures and costs decline, hyperspectral imaging is expected to play an increasingly important role in UAV-based forest assessment workflows.

Seasonal variation significantly influenced classification accuracy, particularly for deciduous species like European aspen. In Study **III**, early spring imagery captured during leaf-flush conditions yielded the best results, supporting the idea that phenological differences can be exploited to improve species discrimination. This aligns with recent findings from Chowdhury et al. (2025), where the highest segmentation accuracy for European aspen was achieved using leaf-off aerial imagery, with an F1-score of 0.573 and Intersection over Union (IoU) of 0.280. These results confirm that early spring, when surrounding trees are still without leaves, offers optimal conditions for detecting aspen crowns in high-resolution imagery. Segmentation performance also improved significantly with tree size, showing the highest accuracy for aspens exceeding 30 cm in DBH. The ability to time data acquisition flexibly is a major strength of UAV-based approaches, allowing for optimization of classification performance based on species' seasonal signatures.

The targeted classification of European aspen and standing dead trees provided important insights for biodiversity monitoring. Aspen, though sparse and often underrepresented in forest inventories, was classified with high accuracy when using multispectral and structural features. Standing dead trees, included in Study **IV**, were effectively distinguished using LiDAR-derived structural metrics, underscoring the value of 3D data for mapping non-living forest components. Few studies have addressed these indicators simultaneously, making this thesis a meaningful contribution to fine-scale ecological assessments in boreal forests.

These findings have broader implications for biodiversity assessment and forest management. UAV-based approaches offer a scalable and flexible alternative to conventional methods, with the potential to deliver high-resolution, species-specific data to support adaptive forest planning and conservation. The integration of ecological indicators such as aspen and deadwood into UAV-based workflows can enhance monitoring strategies and align remote sensing with conservation goals.

Several limitations should be acknowledged. UAV data collection is constrained by flight regulations, weather dependency, and battery life, which can limit spatial coverage of the surveys, particular in large or remote areas. However, recent developments in aerial data collection platforms, such as the autonomous airships deployed by Kelluu Ltd. (2024), offer new possibilities for overcoming spatial limitations. These systems can stay airborne for extended periods and cover large areas with high-resolution sensor payloads, enabling scalable biodiversity monitoring and highlighting the need for efficient processing workflows capable of handling such large, high-detail datasets. Reference data availability also varied, with some areas relying on visual interpretation rather than field measurements. Collecting high-quality field data remains both time-consuming and costly, especially across large or remote areas. However, emerging close-range remote sensing technologies, such as terrestrial laser scanning (TLS), backpack LiDAR, and mobile platforms, offer promising alternatives for acquiring detailed reference data more efficiently (Hyyppä et al., 2020a; Hyyppä et al., 2020b; Liang et al., 2022; Chen et al., 2024). These approaches can reduce dependence on traditional fieldwork while maintaining the accuracy needed for tree-level validation and training data generation.

Crown segmentation accuracy directly impacted classification performance, especially for understory or overlapping trees (Qin et al. 2022; Liu et al. 2023). The classification analyses in this thesis were based on individually measured upper-canopy trees, primarily large and dominant individuals. Suppressed understory trees were not included in the reference datasets, as the focus was on canopy-visible trees and ecologically valuable large aspens. Explicit tree detection statistics were reported in Study IV, where detection performance was specifically evaluated, while in the other studies mismatches between segmented crowns and field-measured trees were excluded from classification analyses rather than treated as detection errors. Consequently, tree detection rates were not harmonized across all studies and are not directly comparable, which should be considered when interpreting cross-study results. In addition, the validation strategies applied across the studies primarily assessed internal consistency within each study area rather than full spatial generalization. Validation approaches included leave-image-out cross-validation, tree-level leave-one-out validation, and stratified random train-test splits. While these methods provide robust internal performance estimates, they do not explicitly account for spatial autocorrelation at the plot or stand level. When training and testing samples originate from nearby trees with similar structural and spectral characteristics, classification accuracy may be moderately inflated. Spatially blocked or cross-site validation designs would provide a more conservative estimate of model transferability across independent forest stands and acquisition conditions. Beyond validation design, transferability of the proposed workflows to new areas depends on forest structure, acquisition timing, and sensor characteristics. While the general workflow components, such as DTM normalization, the use of photogrammetric point clouds for deriving structural metrics and the integration of spectral and structural predictors, are broadly applicable, model performance may degrade when segmentation quality, phenological effects, or radiometric inconsistencies between acquisitions (e.g., illumination, calibration, and sensor response differences) differ from the training environment (Chen et al.2024; Chadwick et al., 2024). Recent studies demonstrate that tree species classification models often lose accuracy when transferred across years, seasons, or sensor configurations, even when based on time-series or multi-source data; using more diverse training data can reduce but not fully eliminate this decline (Verhulst et al., 2024; Huang et al., 2024). These findings highlight that robust generalization requires careful adaptation of acquisition timing, preprocessing workflows, and radiometric harmonization and validation across independent sites when applying models beyond their original study context.

Future work should explore the integration of emerging sensor technologies such as hyperspectral UAVs and full-waveform LiDAR. Advances in deep learning and multi-temporal analysis could further enhance classification accuracy and generalizability. Expanding the study to broader geographic areas and different forest types would help validate the methods at scale. Finally, translating UAV-based monitoring into operational workflows for forest managers and conservation practitioners remains a key priority, especially in the context of biodiversity policy and adaptive forest planning.

CONCLUSION

This thesis demonstrated that UAV-based remote sensing offers an effective and flexible approach to tree species classification and biodiversity monitoring in boreal forests. The integration of spectral and structural data, especially when acquired simultaneously, significantly improves classification accuracy, particularly for ecologically important and sparse indicators like European aspen and standing dead trees. The findings highlight the potential of UAV technologies to complement and enhance traditional forest inventory practices, offering scalable solutions for conservation planning and adaptive forest management.

REFERENCES

Baroni D, Korpimäki E, Selonen V, and Laaksonen T (2020) Tree cavity abundance and beyond: nesting and food storing sites of the pygmy owl in managed boreal forests. For. Ecol. Manage. 460: 117818. http://dx.doi.org/10.1016/j.foreco.2019.117818

Berner LT & Goetz SJ (2022) Satellite observations document trends consistent with a boreal forest biome shift. Glob. Change Biol. 28(10): 3275–3292. https://doi.org/10.1111/gcb.16121

Bradshaw CJA, Warkentin IG, Sodhi NS (2009) Natural stand structures, disturbance regimes and successional dynamics in the Eurasian boreal forests: a review with special reference to Russian studies. Ann. For. Sci. 66, 201. https://doi.org/10.1051/forest/2008083

Carnol M, Baeten L, Branquart E, Grégoire JC, Heughebaert A, Muys B, Ponette Q, Verheyen K (2014) Ecosystem services of mixed species forest stands and monocultures: comparing practitioners' and scientists' perceptions with formal scientific knowledge. Forestry 87: 639–653. https://doi.org/10.1093/forestry/cpu024

Chadwick AJ, Coops NC, Bater CW, Martens LA, White B (2024) Transferability of a Mask R–CNN Model for the Delineation and Classification of Two Species of Regenerating Tree Crowns to Untrained Sites. Sci. Remote Sensing 9:100109. https://doi.org/10.1016/j.srs.2023.100109

Chen J, Liang X, Liu Z, Gong W, Chen Y, Hyyppä J, Kukko A, Wang Y (2024) Tree species recognition from close-range sensing: a review. Rem. Sens. Environ. 313:114337. https://doi.org/10.1016/j.rse.2024.114337

Chowdhury AI, Heinaro E, Tanhuanpää T, Ur Rahman A, Junttila S (2025) Mapping large European aspens (Populus tremula L.) using national aerial imagery and a U-Net convolutional neural network. Remote Sens. Appl.: Soc. Environ, 40:101755. https://doi.org/10.1016/j.rsase.2025.101755

Colomina I, Molina P (2014) Unmanned aerial systems for photogrammetry and remote sensing: A review. ISPRS J. Photogramm. Remote Sens. 92:79–97. https://doi.org/10.1016/j.isprsjprs.2014.02.013

Cosenza DN, Packalen P, Maltamo M, Varvia P, Räty J, Soares P, Tomé M, Strunk JL, Korhonen L (2021) Effects of numbers of observations and predictors for various model types on the performance of forest inventory with airborne laser scanning. Can. J. For. Res. 52(3):385-395. https://doi.org/10.1139/cjfr-2021-0192

Esseen PA, Ehnström B, Ericson L, Sjöberg K (1997) Boreal forests. Ecol. Bull. 46: 16–47. Available from https://www.jstor.org/stable/20113207.

Fan Z, Wei J, Zhang R, & Zhang W (2023) Tree Species Classification Based on PointNet++ and Airborne Laser Survey Point Cloud Data Enhancement. Forests 14(6):1246. https://doi.org/10.3390/f14061246

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

Fassnacht FE, White JC, Wulder MA, Næsset E (2024) Remote sensing in forestry: current challenges, considerations and directions. Forestry 97:11–37. https://doi.org/10.1093/forestry/cpad024.

Fox EW, Hill RA, Leibowitz SG, Olsen AR, Thornbrugh DJ, Weber MH (2017) Assessing the accuracy and stability of variable selection methods for random forest modeling in ecology. Environ. Monit. Assess. 89:316. https://doi.org/10.1007/s10661-017-6025-0

Franklin SE & Ahmed OS (2018) Deciduous tree species classification using object-based analysis and machine learning with unmanned aerial vehicle multispectral data. Int. J. Remote Sens. 39:5236–5245. https://doi.org/10.1080/01431161.2017.1363442

Fraser BT, Congalton RG, & Ducey MJ (2025) Quantifying the Accuracy of UAS-Lidar Individual Tree Detection Methods Across Height and Diameter at Breast Height Sizes in Complex Temperate Forests. Remote Sens. 17(6):1010. https://doi.org/10.3390/rs17061010

Gaines WL, Harrod RJ, Lehmkuhl JF (1999) Monitoring biodiversity: quantification and interpretation. Gen. Tech. Rep. PNW-GTR-443. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. https://doi.org/10.2737/PNW-GTR-443.

Guimaraes N, P´adua L, Marques P, Silva N, Peres E, Sousa JJ (2020) Forestry remote sensing from unmanned aerial vehicles: a review focusing on the data, processing and potentialities. Remote Sens. 12:1046. https://doi.org/10.3390/rs12061046

Haralick RM, Shanmugam K, & Dinstein IH (2007) Textural features for image classification. IEEE Trans. Syst. Man Cybern. 6:610-621.

Hlásny T, König L, Krokene P, Lindner M, Montagné-Huck C, Müller J, et al (2021) Bark beetle outbreaks in Europe: state of knowledge and ways forward for management. Curr. For. Rep. 7:138–165. https://doi.org/10.1007/s40725-021-00142-x

Helfenstein IS, Schneider FD, Schaepman ME, & Morsdorf F (2022) Assessing biodiversity from space: impact of spatial and spectral resolution on trait-based functional diversity. Remote Sens. Environ. 275:113024. https://doi.org/10.1016/j.rse.2022.113024.

Holmgren J, Persson Å, & Söderman U (2008) Species identification of individual trees by combining high resolution LiDAR data with multi-spectral images. Int. J. Remote Sens. 29:1537–1552. https://doi.org/10.1080/01431160701736471

Huang Y, Ou B, Meng K, Yang B, Carpenter J, Jung J & Fei S (2024) Tree Species Classification from UAV Canopy Images with Deep Learning Models. Remote Sens. 16(20):3836. https://doi.org/10.3390/rs16203836

Hyyppä E, Hyyppä J, Hakala T, Kukko A, Wulder MA, White JC, Pyörälä J, Yu X, Wang Y, Virtanen JP, Pohjavirta O, Liang X, Holopainen M, Kaartinen H (2020a) Under-canopy UAV laser scanning for accurate forest field measurements. ISPRS J. Photogramm. Remote Sens. 164, 41–60. https://doi.org/10.1016/j.isprsjprs.2020.03.021

Hyyppä E, Yu X, Kaartinen H, Hakala T, Kukko A, Vastaranta M. & Hyyppä J (2020b) Comparison of Backpack, Handheld, Under-Canopy UAV, and Above-Canopy UAV Laser Scanning for Field Reference Data Collection in Boreal Forests. Remote Sens. 12(20):3327. https://doi.org/10.3390/rs12203327

Hyvärinen E, Juslén A, Kemppainen E, Uddström A & Liukko UM (2019) Suomen Lajien Uhanalaisuus Punainen Kirja (The 2019 Red List of Finnish Species); Ympäristöministeriö (Ministry of the Environment) & Suomen Ympäristökeskus (Finnish Environment Institute): Helsinki, Finland.

Kangas A (2006) Sampling rare populations. In: Forest Inventory. Springer, Dordrecht, p. 119-139.

Kayes I, Mallik A (2020) Boreal Forests: Distributions, Biodiversity, and Management. In: Leal Filho, W., Azul, A., Brandli, L., Lange Salvia, A., Wall, T. (eds) Life on Land. Encyclopedia of the UN Sustainable Development Goals. Springer, Cham. https://doi.org/10.1007/978-3-319-71065-5_17-1

Kelluu Ltd, Hietala J, Jormakka J, Honkavaara E, Koivumäki N, de Oliveira RA, Lyytikäinen, Saarenmaa P, Tuviala J, Maanmittauslaitos, et al (2024) Koli kelluu airship spring 2023. https://doi.org/10.23729/a6e8e2ef-0b72-411c-b011-ceae2d956f3a

Kivinen S, Koivisto E, Keski-Saari S, Poikolainen L, Tanhuanpää T, Kuzmin A, et al (2020) A keystone species, European aspen (Populus tremula L.), in boreal forests: ecological role, knowledge needs and mapping using remote sensing. For. Ecol. Manage. 462: 118008–. http://dx.doi.org/10.1016/j.foreco.2020.118008.

Kouki J, Arnold K and Martikainen P (2004) Long-term persistence of aspen – a key host for many threatened species – is endangered in old-growth conservation areas in Finland. J. Nat. Conserv. 12: 41–52. https://doi.org/10.1016/j.jnc.2003.08.002

Korpela I, Ørka OH, Maltamo M, Tokola T, & Hyyppä J (2010) Tree species classification using airborne LiDAR—Effects of stand and tree parameters, downsizing of training set, intensity normalization, and sensor type. Silva Fennica 44:319–339. https://doi.org/10.14214/sf.156

Kukkonen M, Maltamo M, Korhonen L & Packalen P (2019) Comparison of multispectral airborne laser scanning and stereo matching of aerial images as a single sensor solution to forest inventories by tree species. Remote Sens. Environ. 231:111208. https://doi.org/10.1016/j.rse.2019.05.027

Kukkonen M, Lähivaara T & Packalen P (2024) Combination of lidar intensity and texture features enable accurate prediction of common boreal tree species with single sensor uas data. IEEE Trans. Geosci. Remote Sens. 62:4401508. http://dx.doi.org/10.1109/tgrs.2023.3345745

Kuuluvainen T (2002) Natural variability of forests as a reference for restoring and managing biological diversity in boreal Fennoscandia. Silva Fenn. 36: 97–125. http://dx.doi.org/10.14214/sf.552.

Kuuluvainen T, Aakala T & Várkonyi G (2017) Dead standing pine trees in a boreal forest landscape in the Kalevala National Park, northern Fennoscandia: amount, population characteristics and spatial pattern. For. Ecosyst. 4:12. https://doi.org/10.1186/s40663-017-0098-7

Lausch A, Bannehr L, Beckmann M, Boehm C, Feilhauer H, Hacker JM, ... & Cord AF (2016) Linking Earth Observation and taxonomic, structural and functional biodiversity: Local to ecosystem perspectives. Ecol. Indic. 70:317–339. https://doi.org/10.1016/j.ecolind.2016.06.022

Lee S, Sim W, Lee Y, Park J, Kang J, & Lee J (2025) Comparative Analysis of Machine Learning and Deep Learning Models for Individual Tree Structure Segmentation Using Terrestrial LiDAR Point Cloud Data. Remote Sens. 17(13):2245. https://doi.org/10.3390/rs17132245

Liang X, Kukko A, Balenovic I, Saarinen N, Junttila S, Kankare V, Holopainen M, Mokros M, Surovy P, Kaartinen H, Jurjevic L, Honkavaara E, Nasi R, Liu J, Hollaus M, Tian J, Yu X, Pan J, Cai S, Virtanen JP, Wang Y, Hyyppa J (2022) Close-range remote sensing of Forests: the state of the art, challenges, and opportunities for systems and data acquisitions. IEEE Geosci. Remote Sens. Mag. 10:32–71. https://doi.org/10.1109/MGRS.2022.3168135

Liu Y, You H, Tang X, You Q, Huang Y, & Chen J (2023) Study on Individual Tree Segmentation of Different Tree Species Using Different Segmentation Algorithms Based on 3D UAV Data. Forests, 14(7), 1327. https://doi.org/10.3390/f14071327

Löfroth T, Birkemoe T, Shorohova E, Dynesius M, Fenton NJ, Drapeau P, Tremblay JA (2023) Deadwood Biodiversity. In: Boreal Forests in the Face of Climate Change. Springer, pp. 167–189. https://doi.org/10.1007/978-3-031-15988-6_6

Ma Y, Zhao Y, Im J, Zhao Y, and Zhen Z (2024) A Deep-Learning-Based Tree Species Classification for Natural Secondary Forests Using Unmanned Aerial Vehicle Hyperspectral Images and LiDAR. Ecol. Indic. 159:111608. https://doi.org/10.1016/j.ecolind.2024.111608

Maltamo M, Packalen P (2014) Species identification using airborne laser scanning. In: Forestry Applications of Airborne Laser Scanning. Springer, pp. 135–156. https://doi.org/10.1007/978-94-017-8663-8_7

Maltamo M, Pesonen A, Korhonen L, Kouki J, Vehmas M, & Eerikäinen K (2015) Inventory of aspen trees in spruce dominated stands in conservation area. For. Ecosyst. 2:12. https://doi.org/10.1186/s40663-015-0037-4

Maltamo M, Packalen P, and Kangas A (2021) From comprehensive field inventories to remotely sensed wall-to-wall stand attribute data - a brief history of management inventories in the Nordic countries. Can. J. For. Res. 51(2): 257–266. https://doi.org/10.1139/cjfr-2020-0322

Martikainen P, Penttilä R, Kotiranta H & Miettinen O (2000) New records of Funalia trogii, Perenniporia tenuis and Polyporus pseudobetulinus from Finland, with notes on their habitat requirements and conservation implications. Karstenia 40:79-92. https://doi.org/10.29203/ka.2000.356

Michałowska M, Rapiński J (2021) A Review of Tree Species Classification Based on Airborne LiDAR Data and Applied Classifiers. Remote Sens. 13:353. https://doi.org/10.3390/rs13030353

Mäyrä J, Keski-Saari S, Kivinen S, Tanhuanpää T, Hurskainen P, Kullberg P, Poikolainen L, Viinikka A, Tuominen S, Kumpula T, & Vihervaara P (2021) Tree species classification from airborne hyperspectral and LiDAR data using 3D convolutional neural networks. Remote Sens. Environ. 256:112322. https://doi.org/10.1016/j.rse.2021.112322.

Mäyrä J, Tanhuanpää T, Kuzmin A, Heinaro E, Kumpula T & Vihervaara P (2025) Using UAV images and deep learning to enhance the mapping of deadwood in boreal forests. Remote Sens. Environ. 329:114906. https://doi.org/10.1016/j.rse.2025.114906

Nevalainen O, Koivumäki N, Alves de Oliveira R, Hakala T, Näsi R, Liang X, Wang Y, Hyyppä J, Honkavaara E (2025) Drone imaging-based wall-to-wall processing pipelines for individual tree level inventory in boreal forest plots. ISPRS Open J. Photogramm. Remote Sens. 17:100099. https://doi.org//10.1016/j.ophoto.2025.100099

Nezami S, Khoramshahi E, Nevalainen O, Pölönen I, Honkavaara E (2020) Tree Species Classification of Drone Hyperspectral and RGB Imagery with Deep Learning Convolutional Neural Networks. Remote Sens. 12:1070. https://doi.org/10.3390/rs12071070

Onishi M, Ise T (2021) Explainable identification and mapping of trees using uav rgb image and deep learning. Sci. Rep. 11:903. https://doi.org/10.1038/s41598-020-79653-9

Ørka HO, Dalponte M, Gobakken T, Naesset E & Ene LT (2013) Characterizing forest species composition using multiple remote sensing data sources and inventory approaches. Scand. J. For. Res. 28:677–688. https://doi.org/10.1080/02827581.2013.793386

Paheding S, Saleem A, Siddiqui MFH, Rawashdeh N, Essa A, Reyes AA (2024) Advancing Horizons in remote sensing: a comprehensive survey of deep learning models and applications in image classification and beyond. Neural Comput. Appl. 36:16727–16767. https://doi.org/10.1007/s00521-024-10165-7

Packalén P, Temesgen H & Maltamo M (2007) Variable selection strategies for nearest neighbor imputation methods used in remote sensing based forest inventory. Can. J. Rem. Sens. 38:557–569. https://doi.org/10.5589/m12-046

Patacca M, Lindner M, Lucas-Borja ME, Cordonnier T, Fidej G, Gardiner B, et al (2023) Significant increase in natural disturbance impacts on European forests since 1950. Glob. Change Biol. 29:1359–1376. https://doi.org/10.1111/gcb.16531

Petrou ZI, Manakos I, Stathaki T (2015) Remote sensing for biodiversity monitoring: A review of methods for biodiversity indicator extraction and assessment of progress towards international targets. Biodivers. Conserv. 24:2333–2363. https://doi.org/10.1007/s10531-015-0947-z.

Puliti S, Ørka HO, Gobakken T & Næsset E (2015) Inventory of small forest areas using an unmanned aerial system. Remote Sens. 7: 9632–9654. https://doi.org/10.3390/rs70809632

Puliti S, Lines ER, Müllerová J, Frey J, Schindler Z, Straker A, Allen MJ, Winiwarter L, Rehush N, Hristova H, Murray B, Calders K, Coops N, Höfle B, Irwin L, Junttila S, Krůček M, Krok G, Král K, … Astrup R (2025) Benchmarking tree species classification from proximally sensed laser scanning data: Introducing the FOR-species20K dataset. Methods in Ecol. Evol. 16:801–818. https://doi.org/10.1111/2041-210X.14503

Qin H, Zhou W, Yao Y, Wang W (2022) Individual tree segmentation and tree species classification in subtropical broadleaf forests using Uav-based lidar, hyperspectral, and ultrahigh-resolution Rgb data. Remote Sens. Environ. 280:113143 https://doi.org/10.1016/j.rse.2022.113143

Reddy CS (2021) Remote sensing of biodiversity: what to measure and monitor from space to species? Biodivers. Conserv. 30 (10):2617–2631. https://doi.org/10.1007/s10531-021-02216-5.

Reddy CS, Satish KV, Saranya KRL, Sri Surya NN, Neha PA & Rajashekar G (2024) Harnessing essential biodiversity variables and remote sensing of earth observations-synthesizing biodiversity insights. Spat. Inf. Res. 32(3):265–276. https://doi.org/10.1007/s41324-023-00558-6

Rogers PC, Pinno BD, Šebesta J, Albrectsen BR, Li G, Ivanova N, et al (2020) A global view of aspen: Conservation science for widespread keystone systems. Glob. Ecol. Conserv. 21:e00828. https://doi.org/10.1016/j.gecco.2019.e00828

Saarinen N, Vastaranta M, Näsi R, Rosnell T, Hakala T, Honkavaara E, Wulder MA, Luoma V, Tommaselli AMG, Imai NN, Ribeiro EAW, Guimarães RB, Holopainen M, Hyyppä J (2018) Assessing biodiversity in boreal forests with UAV-based photogrammetric point clouds and hyperspectral imaging. Remote Sens 10:338. https://doi.org/10.3390/rs10020338.

Seidl R, Rammer W (2017) Climate change amplifies the interactions between wind and bark beetle disturbances in forest landscapes. Landsc. Ecol. 32:1485–1498. https://doi.org/10.1007/s10980-016-0396-4

Skidmore AK, Coops NC, Neinavaz E, Ali A, Schaepman ME, Paganini M, ... & Wingate V (2021) Priority list of biodiversity metrics to observe from space. Nat. Ecol. Evol. 5(7):896–906. https://doi.org/10.1038/s41559-021-01451-x

Sothe C, Dalponte M, Almeida CMD, Schimalski MB, Lima CL, Liesenberg V, Miyoshi GT, and Tommaselli AM (2019) “Tree Species Classification in a Highly Diverse Subtropical Forest Integrating UAV-Based Photogrammetric Point Cloud and Hyperspectral Data.” Remote Sens. 11:1338. https://doi.org/10.3390/rs11111338.

Tikkanen OP, Martikainen P, Hyvärinen E, Junninen K & Kouki J (2006) Red-listed boreal forest species of Finland: associations with forest structure, tree species, and decaying wood. Ann. Zool. Fennici 43(4):373–383.

Toivonen J, Kangas A, Maltamo M, Kukkonen M, Packalen P (2023) Assessing biodiversity using forest structure indicators based on airborne laser scanning data. For. Ecol. Manag. 546:121376. https://doi.org/10.1016/j.foreco.2023.121376

Toivonen J, Kangas A, Maltamo M, Kukkonen M & Packalen P (2024) Mapping large European aspen (Populus tremula L.) in Finland using airborne lidar and image data. Can. J. For. Res. 54(7):762-773. https://doi.org/10.1139/cjfr-2023-0271

Torresan C, Berton A, Carotenuto F, Di Gennaro SF, Gioli B, Matese A, Miglietta F, Vagnoli C, Zaldei A, & Wallace L (2017) Forestry applications of UAVs in Europe: A review. Int. J. Remote Sens. 38:2427–2447. https://doi.org/10.1080/01431161.2016.1252477

Tuominen S, Näsi R, Honkavaara E, Balazs A, Hakala T, Viljanen N, Pölönen I, Saari H, Ojanen H (2018) Assessment of classifiers and remote sensing features of hyperspectral imagery and stereo-photogrammetric point clouds for recognition of tree species in a forest area of high species diversity. Remote Sens. 10:714. https://doi.org/10.3390/rs10050714.

Vauhkonen J, Ene L, Gupta S, Heinzel J, Holmgren J, Pitkänen J, Solberg S, Wang Y, Weinacker H, Hauglin KM, et al (2012) Comparative testing of single-tree detection algorithms under different types of forest. Forestry 85: 27–40, https://doi.org/10.1093/forestry/cpr051

Vauhkonen J, Ørka HO, Holmgren J, Dalponte M, Heinzel J, Koch B (2013) Tree species recognition based on airborne laser scanning and complementary data sources. In: Forestry Applications of Airborne Laser Scanning. Springer, pp. 135–156. https://doi.org/10.1007/978-94-017-8663-8_7.

Verhulst M, Heremans S, Blaschko MB, Somers B (2024) Temporal transferability of tree species classification in temperate forests with Sentinel-2 time series. Remote Sens. 16:2653. https://doi.org/10.3390/rs16142653

Viinikka A, Hurskainen P, Keski-Saari S, Kivinen S, Tanhuanpää T, Mäyrä J, Poikolainen L, Vihervaara P & Kumpula T (2020) Detecting European aspen (Populus tremula L.) in boreal forests using airborne hyperspectral and airborne laser scanning data. Remote Sens. 12:2610. https://doi.org/10.3390/rs12162610.

Vorster AG, Evangelista PH, Stovall AEL et al (2020) Variability and uncertainty in forest biomass estimates from the tree to landscape scale: the role of allometric equations. Carbon Balance Manag. 15:8. https://doi.org/10.1186/s13021-020-00143-6

Xing D, Bergeron JAC, Solarik KA, Tomm B, Macdonald SE, Spence JR, He F (2019) Challenges in estimating forest biomass: use of allometric equations for three boreal tree species. Can. J. For. Res. 49(12):1613–1622. https://doi.org/10.1139/cjfr-2019-0258

Zhang H, Liu B, Yang B, Guo J, Hu Z, Zhang M, Yang Z & Zhang J (2025) Efficient tree species classification using machine and deep learning algorithms based on UAV-LiDAR data in North China. Front. For. Glob. Change 8:1431603. https://doi.org/10.3389/ffgc.2025.1431603

Zhang Z, Huang L, Wang Q, Jiang L, Qi Y, Wang S, Shen T, Tang BH, Gu Y (2025) UAV Hyperspectral Remote Sensing Image Classification: A Systematic Review. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.18:3099–3124. https://doi.org/10.1109/JSTARS.2024.3522318

Zhong H, Lin W, Liu H, Ma N, Liu K, Cao R, Wang T, and Ren Z (2022) Identification of Tree Species Based on the Fusion of UAV Hyperspectral Image and LiDAR Data in a Coniferous and Broad-Leaved Mixed Forest in Northeast China. Front. Plant Sci. 13:964769. https://doi.org/10.3389/fpls.2022.964769.

Zhong H, Zhang Z, Liu H, Wu J, & Lin W (2024) Individual Tree Species Identification for Complex Coniferous and Broad-Leaved Mixed Forests Based on Deep Learning Combined with UAV LiDAR Data and RGB Images. Forests 15(2):293. https://doi.org/10.3390/f15020293

Zhu H, Song W, Zhang B, Lu E, Dai J, Zhao W, Hu Z (2025) Studying forest species classification methods by combining PolSAR and vegetation spectral indices. Forests 16:15. https://doi.org/10.3390/f16010015.