

Urban Tree Classification in Delft, the Netherlands

Classifying Urban Tree Characteristics with
Machine Learning Using Airborne LiDAR and
Satellite Imagery

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**Classifying Urban Tree Characteristics with Machine
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by

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Preface

In the forest of life, we often find that the random paths lead to the most beautiful trees.

This master thesis represents the culmination of my master studies at the Geoscience and Remote Sensing department of TU Delft. From the outset, I had a deep-seated interest in the intersection of remote sensing, machine learning, and vegetation monitoring. I am immensely grateful to have concluded my time at TU Delft with research that aligns so perfectly with these interests.

I would like to express my sincere gratitude to my supervisors, Roderik, Marc, and Azarakhsh, for their unwavering support, time, and energy throughout this study. Roderik was deeply involved throughout the research process, always available to provide kind support and invaluable feedback. His continuous enthusiasm was contagious, making our collaboration a great pleasure. I am especially grateful for his ongoing guidance and patience. Marc offered essential feedback and consistently provided excellent advice, while Azarakhsh brought a fresh perspective to the research, broadening my view and enhancing the study's depth.

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*Lina Hagenah
Delft, July 2024*

Abstract

Current urban tree inventories rely heavily on time-consuming manual work and often fail to capture all trees. To effectively monitor the impact of urban trees on their environment and vice versa, an automated method for detecting and grouping trees based on their characteristics is crucial. This research aims to expand current urban tree inventories and cluster trees based on their characteristics. Existing inventories typically include species, age, and height, but trees of the same species and age can vary significantly due to environmental factors. This study focuses on a 500x600 meter area in Delft, encompassing 641 recorded trees from the municipal inventory.

An automatic tree detection method using airborne LiDAR (AHN4) point cloud data combined with Random Forest classification was implemented, achieving an accuracy of 85-90%. Individual trees were identified using an existing tree segmentation algorithm, detecting 70% of recorded trees with a mean location difference of 0.71 meters and identifying an additional 460 trees, including those on private land. Despite promising results, limitations include the undetection of small trees (below 3 meters) and classification errors leading to missed detections, multiple identifications for single trees, and false positives. Geometric and reflectance features were extracted. High-resolution, 30cm, spectral images from the SuperView Neo satellites, acquired across three seasons, provided spectral features like tree color and NDVI. Overall resulting in a total of 50 features. This comprehensive inventory allows for clustering of individual trees based on geometric, reflectance, and spectral similarities using a K-means algorithm.

The approach enhances urban tree inventories by incorporating new features from airborne LiDAR and spectral images, such as tree height distribution, crown sphericity, and density. Seasonal changes from spectral images provide insights into tree behavior. These detailed features significantly improve clustering, effectively grouping similar trees together.

The findings reveal that trees of the same species in seemingly similar environments exhibit significantly different characteristics. This research offers a method to enhance urban tree inventories and supports long-term studies to reveal how trees respond to urban development, climate change, and ecological dynamics. Correlating tree growth and health with specific locations and climatic conditions can aid in developing sustainable urban planning and conservation strategies.

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1 Summary

This research describes and evaluates an automated method for detecting and characterizing urban trees in Delft offering insights crucial for urban biodiversity, aesthetics, and future planning.

This research centers on a 500x600 meter area in Delft, covering 641 recorded trees from the Delft municipal inventory. The study uses airborne LiDAR (AHN4) data and applies a Random Forest classification to achieve a relatively high tree classification accuracy (85-90%). The Individual Tree Detection (ITD) method applied identifies 70% of recorded trees with a mean location difference of 0.71 meters and discovers 460 additional trees, including those on private land. Challenges include occasional failure to detect small trees and errors in tree identification stemming from classification inaccuracies and limitations in detection parameters. Achievements include successfully identifying private trees, improving tree location accuracy, and uncovering discrepancies in the existing tree inventory.

From LiDAR data, geometric features and reflectance features are extracted. Validation of detected tree heights against trees from the Delft Municipality Tree Inventory estimates showed a mean difference of approximately 2.6 meters. One significant finding of this study is the use of geometric features such as tree sphericity. It's important to note that sphericity measurements, derived from LiDAR data collected during the leaf-off season, may not fully represent tree characteristics throughout the year. Furthermore, a correlation was observed between point density, maximum height, and sphericity, indicating that dense and tall trees tend to exhibit higher sphericity values. High-resolution spectral images, with a 30cm resolution, from the SuperView Neo satellites capture tree color and NDVI across three seasons, spring, summer and fall. Variations in RGB values and NDVI indicate seasonal changes in foliage density and health, critical for assessing urban green spaces' vitality and resilience.

The integration of LiDAR and spectral data enables K-means clustering, which improves tree characterization using ALS (Airborne Laser Scanning) and MS (Multispectral) features. Smaller cluster sizes demonstrate the potential to group trees based on common traits, yielding promising implications. This method enriches urban tree inventories by integrating new attributes derived from airborne LiDAR and spectral images, including tree height distribution, crown sphericity, and density. Seasonal fluctuations observed in spectral images provide critical insights into tree dynamics, thereby improving the tree clustering by effectively grouping trees with similar characteristics.

This research holds significant potential for enhancing tree inventory systems, like the Delft Municipality Tree Inventory, by integrating automated, precise methodologies. Traditionally reliant on time-consuming and less accurate manual recordings, these inventories can now benefit from automated techniques for frequent updates and comprehensive data. This approach supports urban tree biodiversity evaluation, environmental impact assessment, and aesthetic planning by grouping trees with similar characteristics, thereby aiding efficient analysis and management of urban forests.

Suggestions for improvement encompass enhancing classification algorithms, adapting ITD to accommodate tree variability, validating methods through meticulous fieldwork, and integrating advanced technologies with current tree inventories. Ongoing monitoring and regular updates to databases are essential for comprehensive urban forestry management and sustainability.

Nomenclature

Abbreviations

AHN	Actueel Hoogtebestand Nederland (Current Height File Netherlands)
ALS	Airborne Laser Scan
DSM	Digital Surface Model
DTM	Digital Terrain Model
GPS	Global Positioning Service
IMU	Inertial Measurement Unit
ITD	Individual Tree Detection
LiDAR	Light Detection and Ranging
LSSM	Least Squares Surface Matching
LZD	Least Z-Difference algorithm
MS	Multispectral Imagery
NDVI	Normalized difference vegetation index
NIR	Near-infrared
NSO	Netherlands Space Office
PCA	Principal Component Analysis
ppm	Parts per million
RF	Random Forest
RGB	Red, Green, Blue
SVM	Support Vector Machine

2 Introduction

Amidst the city's structured chaos, there is a hidden beauty in the harmonious patterns of urban trees.

This research paper highlights the importance of urban tree monitoring. It begins by outlining the context and motivation behind the study, followed by the research questions and objectives. Additionally, it presents the general approach used to address these questions.

2.1 Context and Motivation

In recent years the interest in monitoring urban vegetation has increased (Uçar et al., 2020). Urban trees play a pivotal role in enhancing biodiversity, urban climate moderation, and public health. The selection of tree species affects biodiversity and CO₂ intake, crucial for research and environmental management (Kendal et al., 2018; Livesley et al., 2016). Tree height and crown shape are instrumental in cooling urban environments by providing shade and reducing heat island effects, which also impacts wind patterns in urban areas (Livesley et al., 2016; Rahman et al., 2020). Additionally, tree health and maintenance practices determine the longevity and effectiveness of these benefits, emphasizing the need for municipal oversight (Salmond et al., 2016; Wolf et al., 2020). Ownership affects accessibility and distribution of green spaces, influencing public use and ecosystem services (Brandt et al., 2016). Moreover, considerations such as allergens highlight the importance of tree species and age in public health contexts (Wolf et al., 2020). Thus, a strategic approach to urban forestry, considering these aspects, is essential for sustainable urban development.

This study focuses on the urban trees located in Delft, the Netherlands. Delft is known for its city's infrastructure where the historical charm blends with modern advancements. It has many dutch channels and trees in the core of the city. While some vegetation is rather old, with new developments new trees are planted. In summary, Delft's tree biodiversity and its management are subjects of extensive research, reflecting the city's commitment to environmental sustainability and scientific advancement. This study contributes to a deeper understanding of urban tree biodiversity, crucial for sustainable urban planning and ecological conservation in Delft and the Netherlands.

Tree classification is important in urban areas because different trees have varying advantages and disadvantages. Urban trees provide many benefits, such as improving air quality, mitigating noise pollution, and providing shade and habitat for wildlife (Livesley et al., 2016). The ability to regulate temperature and relative humidity is closely related to tree species (Tan et al., 2016; Livesley et al., 2016), making accurate classification crucial for sustainable urban development and management. Conversely, some trees may damage infrastructure or have invasive roots (Randrup et al., 2001). Root damage or health hazards due to allergens can be evaluated if tree species and their growth and seasonal cycles are known (Salmond et al., 2016). By knowing the classifications of trees, urban planners and landscape managers can choose the most suitable trees to plant. Currently, this can be achieved through tree inventories, which provide data on tree species, age, and location.

With increasing temperatures in the Netherlands due to climate change, the urban heat island effect can be mitigated by introducing more vegetation into cities. If more trees are planted, the

manual tracking of tree inventories will become increasingly time-consuming. These inventories typically exclude trees on private land. Using machine learning to classify trees would significantly reduce manual labor and allow for continuous tracking of individual trees. This could include monitoring tree heights and crown shapes, which would help evaluate their effects on noise pollution, temperatures, and CO2 sequestration in the city (Brandt et al., 2016).

Urban forestry plays a crucial role in enhancing the environmental and aesthetic quality of cities such as Delft. Expanding current tree inventories to include more comprehensive data on private trees and various tree features is essential. Traditionally, manual surveying has been the primary method for collecting tree data. However, this approach is labor-intensive and time-consuming. Many cities lack comprehensive and current tree inventories, a challenge that’s particularly pronounced in larger urban areas. Traditional on-ground methods struggle to keep pace with the vast number of trees and their dynamic changes (Ma et al., 2021). Consequently, many cities opt for partial inventories, such as focusing only on trees along main streets, thereby neglecting a holistic understanding of urban forestry. This issue is even more prominent in smaller urban areas, where tree inventories might be nonexistent (Ma et al., 2021).

While much of the existing research has centered on identifying tree species often using supervised classification, this study aims to group trees based on similar characteristics such as size, color, and crown density. Understanding these groups is vital for assessing their impact on wind patterns, shade provision, and leaf litter. This approach acknowledges that trees of the same species can exhibit significant variations in different environments, especially between managed and unmanaged urban settings, leading to diverse environmental influences.

Identifying groups of trees with similar features is important for evaluating their aesthetic contributions, shade creation, and overall influence on the urban environment. The geometry, color, and health of trees are critical factors that affect their impact on urban climates. In future research, analyzing trees’ influence on urban temperatures, wind behavior, and general climate conditions will benefit from knowledge about the distribution and characteristics of similar trees. This information is essential for comprehensive urban planning and environmental management.

2.2 Research Question and Objective

My research addresses the current challenges in urban tree monitoring by leveraging remote sensing data and machine learning techniques to automate urban tree monitoring. This approach aims to create more detailed and comprehensive urban tree inventories, with a specific focus on grouping trees based on similar characteristics.

The objectives of my research are threefold:

- *Detect Urban Trees:* Develop a method for accurate detection of urban trees using remote sensing data.
- *Extract Valuable Tree Features:* Identify and extract key features of trees, such as crown density, color, and height, to enhance current tree inventories.
- *Unsupervised Clustering:* Implement unsupervised clustering techniques to group trees with similar characteristics, facilitating a deeper understanding of urban forest composition.

By addressing these objectives, my research aims to provide a scalable and efficient solution for

urban tree monitoring, which is crucial for effective urban planning and environmental management.

The main research question for this project is:

To what extent can urban tree characteristics be identified from airborne LiDAR and spectral satellite data using machine learning?

This research question is further separated in sub-questions:

1. What tree groups in urban areas should be characterized, and what are the ecological, aesthetic, and urban planning factors driving their relevance?
2. How to extract tree location from airborne LiDAR and the spectral data?
3. What relevant tree characteristics can be retrieved from airborne LiDAR and spectral satellite data?
4. How does the combination of tree features from LiDAR and spectral satellite data drive the tree characterization?
5. What is the practical utility of the tree characterizations?

This research focuses on the application of automatic tree detection techniques, which can significantly reduce the need for manual surveying. Remote sensing has been widely used in urban forest surveys (Niedzielko et al., 2024; Chi et al., 2021). With increasing vegetation and biodiversity in cities the use of remote sensing to classify trees in urban areas is increasing. The aim of this study is to use large scale datasets such as the Actueel Hoogtebestand Nederland (Current Height File Netherlands, AHN) and high resolution satellite imagery to evaluate urban tree characteristics. Different trees have different spectral and geometric characteristics. Using multi-spectral and LiDAR data to classify trees by applying machine learning algorithms is the goal of this study. The focus will lie on using machine learning to classify tree characteristics as it is often more convenient compared to traditional classification algorithms (Schenk & Csathó, 2002; Alonzo et al., 2014). This automated approach not only aids in the identification and evaluation of trees but also allows for a detailed assessment of tree health by analyzing crown density, color, height growth, and other critical features.

The research approach involves the following steps:

Extracting Tree Information

The first objective is to extract tree information from AHN data. While this is not the main focus of the research, a substantial amount of time will be taken to ensure satisfactory results. Once the trees are segmented from the data, they will be further divided into individual trees using an existing tree segmentation algorithm. The performance of this method will be evaluated through case studies.

Creating a Detailed Urban Tree Inventory

After the detection of individual trees, the next objective is to create a detailed urban tree inventory with more comprehensive tree features. Geometric and reflective tree features will be extracted from the AHN data, while spectral tree features for different seasons will be added using satellite images.

Clustering Trees Based on Characteristics

Finally, these features will be used to cluster the trees based on their characteristics. The performance of the clustering will be evaluated by manually analyzing them through case studies to determine their utility.

3 Background

Past research offers valuable insights into the utilization of LiDAR and spectral data combinations for tree classification. While a significant portion of this research relies on supervised classification techniques to identify tree species, it also sheds light on the various tree features that can be extracted for classification purposes.

3.1 Combining LiDAR and Spectral Data for Enhanced Classification

3.1.1 Case Studies in Diverse Environments

A notable study conducted in the South Eastern alpine region of France, encompassing approximately 1.3 square kilometers of predominantly unmanaged forests, utilized high-density LiDAR data along with 15x15cm aerial RGB imagery and WorldView-2 multispectral imagery at 2x2m resolution with 8 bands and a 0.5x0.5m panchromatic band (Kukunda et al., 2018). The aim was to classify the tree species in this area using Random Forests with cross-validation, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) (Kukunda et al., 2018). The integration of both LiDAR and spectral variables was found to significantly enhance the differentiation capabilities, attributed to the comprehensive capture of various characteristics of tree crowns by the two datasets (Kukunda et al., 2018).

3.1.2 Urban Areas and Managed Trees

Research has not been limited to forested areas; studies have also been conducted in urban settings with managed trees. For instance, a study at York University’s Keele campus in Toronto, Canada, utilized high-resolution multispectral imagery from WorldView-2 and LiDAR data to classify primary tree species including maple, ash, pine, spruce, and locust trees (Li et al., 2020). The study employed deep Convolutional Neural Network (CNN) models, demonstrating superior classification accuracies compared to traditional methods such as Support Vector Machine (SVM) and Random Forest (RF), highlighting the potential of deep learning models in tree species classification (Li et al., 2020). Another study utilizing hyperspectral images and airborne LiDAR showed a automated way of urban tree feature extraction in Poland (Niedzielko et al., 2024).

3.1.3 Challenges and Potential of Unsupervised Classification

While supervised classification methods have shown promising results, they are heavily reliant on the quality of training data, which can be affected by factors such as human error and environmental changes. The potential for unsupervised classification methods to bypass these challenges by eliminating the need for extensive manual labeling is an area worth exploring.

Clustering biodiversity structures, such as tree clustering, presents unique challenges due to their complex and organic composition, which is significantly influenced by environmental factors (Chaovitwongse et al., 2009). This variability poses difficulties but also offers opportunities to identify where and how these environmental factors impact biological networks. By understanding these influences, researchers can better analyze ecological patterns and develop strategies to address the effects of environmental changes on biodiversity.

3.2 Case Studies Highlighting the Importance of Data Integration

3.2.1 Brussels, Belgium

A study in Brussels, Belgium, utilized LiDAR data with a point density of $15/m^2$ and hyperspectral data with a spatial resolution of 2 meters to identify nine dominant broad-leaved trees. The study achieved notable accuracy in delineating individual trees and classifying tree genera, underscoring the significance of integrating LiDAR intensity, height, and hyperspectral data for tree classification (Chi et al., 2021).

This study highlights the importance of enhancing urban tree inventories and demonstrates the effectiveness of using LiDAR and hyperspectral data to extract tree features for species classification.

3.2.2 Missouri, USA

Similarly, a study in an urban public park in Missouri, USA, utilized WorldView-2 and WorldView-3 imagery along with LiDAR data to classify eight urban tree species. The study highlighted the effectiveness of data fusion, with DenseNet models achieving remarkable classification accuracies, especially when combining various data sources (Hartling et al., 2019).

This research demonstrates that Random Forest (RF) outperforms Support Vector Machine (SVM) in tree classification. Additionally, it showcases improvements in classification accuracy using deep learning models like DenseNet (Hartling et al., 2019). The study also highlights the advantages of combining LiDAR and hyperspectral data for enhanced tree species classification, where an increase in species classification accuracy was noted across all different implemented methods.

3.3 Improvements Using Spectral Data

Further research, such as a study conducted in Florida, USA, has indicated the benefits of using spectral data, particularly when combined with seasonal imagery and light normalization techniques, for improving tree species classification accuracy (Pu et al., 2018).

The integration of LiDAR and spectral data has proven to be a powerful tool in tree classification, offering improved differentiation capabilities and highlighting the potential for advanced classification methods. Future research should continue to explore data integration techniques and the potential of unsupervised and semi-supervised learning models to address the challenges of manual labeling and data quality.

3.4 Dutch Tree Archives

In the Netherlands some research was performed regarding detecting trees automatically. For instance there is the Boomregister.nl which is a record of all the trees in the Netherlands based on at least one elevation model and five to six detailed satellite images of the Netherlands. The database is updated within four months upon receiving new images. The tree canopy cover is over 95% complete, with under 2% of objects mistakenly identified as tree crowns. However, accuracy decreases for smaller trees (under 9m in height and 4m in crown diameter) (Boom Register, 2018). Tree height is calculated with a precision of 1.50 meters for 90% of the trees, measured from the trunk base to the upper crown's center of gravity (Boom Register, 2018). This precision does not extend to smaller trees below the specified size thresholds. This database is only visible on

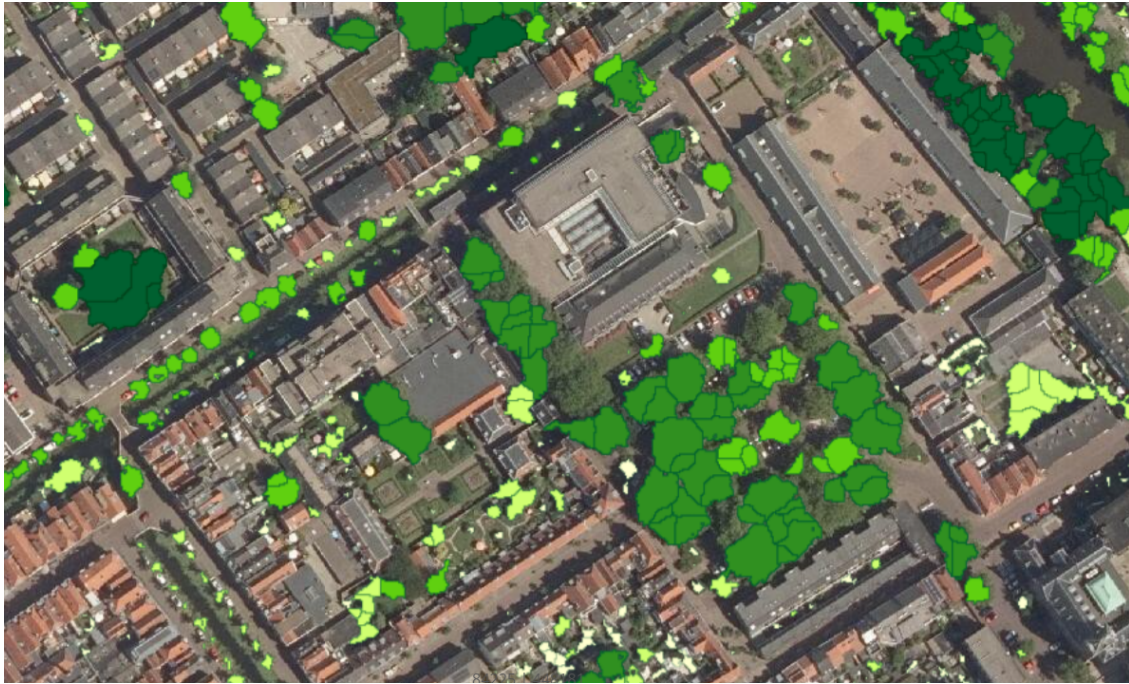


Figure 3.1: Snapshot of the tree detection from Boomregister.nl showing the tree polygons colored based on the tree height with an aerial image as a background. Snapshot is of the Paardenmarkt and surroundings in Delft

the website but it not freely accessible. There is also a website to record important trees in the Netherlands called bomenstichting.nl. The recorded trees are older than 80 and have a life expectancy of 10 more years and lastly specific attribute such as rarity or cultural/historical value ([Bomenstichting, n.d.](http://bomenstichting.nl)).

Amsterdam has more than 1 million trees from which 300,000 are managed by the municipality. These trees are recorded and categorized in different maps; Trees under management, Special trees, Main tree structure, Replaced trees, etc. ([Gemeente Amsterdam, n.d.](http://gemeenteamsterdam.nl)). This is a similar dataset to the Delft Municipality Tree Inventory.

Currently there is development in creating a tree atlas for Delft, that includes tree further tree characteristics but is still limited to municipality owned trees ([Technische Universiteit Delft, 2023](http://technischeuniversiteitdelft.nl)). Additionally, the Atlas will contain maps of Delft and its surroundings that illustrate the historical development of trees and their associated 'forest types' ([Technische Universiteit Delft, 2023](http://technischeuniversiteitdelft.nl)). These maps cover the period from the 16th to the 21st century.

3.5 Research Gap and Trend

While previous research provides a valuable foundation for the main objectives of this study, it's important to acknowledge the significant distinctions that set this research apart. Prior studies often share common goals related to tree species classification, but they frequently differ in several key aspects.

Tree classification from airborne LiDAR or satellite imagery is often conducted in diverse areas with varied vegetation. Many studies have focused on both forest and urban environments, consistently highlighting the benefits of combining LiDAR and spectral data for improved classification

accuracy. Recent research emphasizes enhancing urban tree classification using newer technologies, which is crucial for urban planning and management.

Past research highlights the use of a combination of airborne LiDAR and spectral data for tree identification. However, a notable gap in these previous endeavors is the absence of seasonal data from the spectral datasets. This research, on the other hand, strives to address this gap by incorporating seasonal variations from spectral data sources. Moreover, while earlier research predominantly relied on spectral data with a resolution of 2 meters, this study aims to leverage the finer resolution of seasonal spectral images at 30cm, which can be extracted from the SuperView NEO satellites. This finer resolution is expected to provide more detailed and accurate information for tree classification.

A compelling trend that emerges from the existing body of research is the utility of combining diverse data sources. In this context, there is a significant potential advantage in not only incorporating single spectral images but also diverse seasonal and climate-specific spectral data for tree classification. The inclusion of data from various seasons and climatic conditions can enhance the accuracy and robustness of tree classification models, especially in regions with dynamic environmental conditions.

A second notable divergence is the exploration of clustering individual trees, as demonstrated in the study aimed at classifying two tree species in a French forest [Kukunda et al. \(2018\)](#). This endeavor encountered challenges stemming from variations in species due to factors such as growth stages, age, health, and other environmental influences. Additionally, the resolution of spectral data emerged as a critical factor influencing the efficacy of tree clustering. There is a gap in current research regarding tree grouping based on characteristics that could aid in understanding future urban tree influences on urban environments and vice versa.

While past research primarily focuses on extracting features to distinguish between different tree species, relatively less attention has been directed towards classifying trees into different groups based on their shared characteristics. This study seeks to bridge this gap by exploring the classification of tree groups based on their distinctive traits, particularly in urban environments. Understanding the classification of tree groups can have practical applications in urban planning and ecological studies, providing insights into the composition and health of urban green spaces.

In summary, while prior research provides valuable insights, this study distinguishes itself through its focus on urban environments, the incorporation of seasonal spectral data, finer spectral data resolution, and the exploration of tree group classification, adding a fresh perspective and practical relevance to tree characterization in urban areas.

3.6 Tree characteristics

Deciduous trees can have a variety of characteristics. These can be identified in different ways. Some characteristics such as the bark color, bark texture, fall, color, foliage color and foliage shape can be visually inspected. Furthermore the tree height, shape, growth rate and flower time can be measured. Other factors such as biogenic emissions, health hazards due to pollen generation, pest resistance and susceptibility and root damage potential are harder to evaluate ([UFEI, n.d.](#)).

3.6.1 Tree Height

Tree height is crucial both ecologically and for urban planning. Tracking tree growth aids in identifying animal habitats and planning future urban forest development (Livesley et al., 2016). Taller trees provide more extensive shading, which can cool urban areas and create habitats for various animal species (Rahman et al., 2020; Salmond et al., 2016). Understanding tree height is important for planning urban forests, as it affects shading, which influences microclimates and energy consumption in nearby buildings. Proper planning can enhance cooling effects and reduce energy costs (Rahman et al., 2020).

The distribution of tree height is a critical parameter for distinguishing between different tree species (Kim et al., 2011). It also offers valuable insights into the crown geometry and growth patterns of trees. Understanding these aspects helps in assessing tree health, ecological impact, and the role of trees in urban environments. By analyzing height distribution, researchers can infer various structural characteristics and predict how trees will interact with their surroundings, providing essential information for urban planning and environmental management. Especially by adding the 75th percentile height, the tree species classification can be greatly improved (Niedzielko et al., 2024). The minimum crown height also provides significant information, particularly regarding urban spaces where the area below trees is often utilized.

3.6.2 Tree Crown Geometry

Tree crown geometry, which includes shape and branch structure, holds ecological significance by influencing shading and CO₂ absorption, thereby affecting urban climate regulation (Rahman et al., 2020). The crown width at the median height plays a crucial role in defining tree geometry, influencing its overall shape and structure. The crown width and median height is shown to be a key tree feature in driving tree species classification (Alonzo et al., 2014). This measurement is particularly important because it reflects how the crown spreads horizontally around the tree's median point of height. Understanding crown width helps in assessing the tree's canopy coverage, which is vital for evaluating its ecological function, such as shade provision, carbon sequestration, and habitat for wildlife. Detailed knowledge of tree geometry helps optimize urban cooling strategies (Washington State Department of Natural Resources, 2016). Trees with specific crown shapes can be strategically planted to improve airflow and temperature regulation in urban environments, enhancing overall comfort and reducing urban heat island effects (Rahman et al., 2020).

3.6.3 Tree Crown Intensity

Tree crown intensity values derived from LiDAR data are crucial for assessing tree health, structural integrity, and ecological impact in various environmental studies (Kim et al., 2011). These intensity values provide insights into the density and distribution of foliage within the tree canopy, aiding in the identification of stressed or healthy trees and facilitating precise measurements of canopy cover and biomass estimation.

Past research has demonstrated that LiDAR intensity values play a pivotal role in the classification of tree species (Kim et al., 2011). They serve as valuable features that distinguish between different types of vegetation based on their unique reflectance properties and canopy structures (Marrs & Ni-Meister, 2019). By analyzing these intensity values, researchers can effectively classify tree species and categorize trees with similar properties or canopy structures, thereby contributing to biodiversity assessments, habitat monitoring, and forest management strategies.

3.6.4 Tree Crown Color

Tree color is important aesthetically, enhancing urban landscapes and helping design visually appealing green spaces (Uçar et al., 2020). It is essential for designing attractive urban areas that improve residents' quality of life. Ecologically, color indicates tree health and photosynthetic activity, which are critical for assessing the quality of urban green spaces (Yang et al., 2017). Healthy trees contribute more effectively to urban biodiversity and environmental quality. From an urban planning perspective, selecting tree species that complement the existing aesthetic of urban areas is significant for cohesive landscape design. Color can be used to create visually appealing and diverse urban green spaces.

3.6.5 Tree Crown Number of Returns

The number of returns from LiDAR data is a valuable metric for classifying trees and understanding their structural characteristics. This metric refers to the count of laser pulses reflected back to the LiDAR sensor from different surfaces within the tree canopy and terrain, see Figure 4.2 (ESRI, 2021).

Firstly, the number of returns provides insights into the vertical structure and complexity of tree canopies. Trees with dense foliage and complex branching patterns tend to generate more returns as laser pulses interact with multiple canopy layers and branches (ESRI, 2021). In contrast, sparse canopies or open-grown trees may produce fewer returns.

Secondly, this metric aids in distinguishing between tree species and assessing vegetation density. Different tree species exhibit varying canopy structures and foliage densities, influencing the number of returns recorded by LiDAR (Marrs & Ni-Meister, 2019). High-return counts often indicate dense, multi-layered canopies typical of broad leaf species, while low returns may suggest coniferous species or sparse vegetation (Holmgren et al., 2008; Kukunda et al., 2018).

Additionally, the number of returns supports habitat mapping and biodiversity assessments by identifying structural diversity within forested areas. It assists in quantifying canopy cover, estimating biomass, and monitoring habitat suitability for wildlife.

By analyzing this metric, researchers can enhance tree species classification accuracy (Alonzo et al., 2014; Itakura & Hosoi, 2019) and inform conservation efforts, sustainable forest management practices, and ecosystem monitoring.

3.6.6 Tree Species

Tree species are critical for several reasons. Understanding different tree species helps prevent infrastructure damage from root systems and manage potential allergen risks (Randrup et al., 2001). It is essential for maintaining biodiversity and ecosystem health. Species diversity is crucial for resilience and sustainability in urban forests (Kendal et al., 2018). Diverse tree species can optimize CO₂ intake, reduce allergen risks, and contribute to a balanced urban ecosystem (Wolf et al., 2020; Uçar et al., 2020).

3.6.7 Tree Age

Tree age provides insights into the biodiversity and growth patterns of urban forests. Monitoring age distribution helps understand lifecycle dynamics and plan for succession in urban forests (Ma et

al., 2021). Ensuring a balanced age distribution in urban forests is crucial for long-term resilience. Young trees need to be planted regularly to replace aging ones, maintaining a continuous canopy cover and ecological balance.

3.6.8 Tree Health

Monitoring tree health is vital for predicting and preventing disease outbreaks and assessing environmental stressors (Yang et al., 2017; Salmond et al., 2016). Healthy trees are more resilient and contribute positively to urban biodiversity. Strategies can be developed to enhance tree health and mitigate potential future issues. Understanding the health of urban trees helps in planning maintenance and conservation efforts, ensuring the longevity of urban forests.

3.6.9 NDVI

Vegetation indices also give further information about the tree characteristics. Red and Near-Infrared (NIR) bands allows for the computation of the Normalized Difference Vegetation Index (NDVI). The vegetation indices such as NDVI can be of great use to distinguish between different trees (Hartling et al., 2019).

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (1)$$

NDVI values range from -1 to 1, indicating various health statuses of the vegetation. Typically, a higher NDVI value reflects a greater density and health of the plant's photosynthetic activity (Yang et al., 2017). The NDVI is an indicator of the greenness, the chlorophyll content, of the plant and can give insights into the plants health, density as well as growth state. Negative values indicates an unhealthy plant, or leaves that are about to fall. High values, up to 1, are suggesting a healthy mature leaf. Including spectral tree features such as the NDVI has proven to be highly relevant in urban tree monitoring research due to its ability to provide valuable insights into tree health, foliage density, and seasonal variations (Hartling et al., 2019).

4 Data

While trees can be captured at a high resolution with terrestrial laser scanners, drones or mobile laser scanners, this research focuses on large scale data such as the Actueel Hoogtebestand Nederland (Current Height File Netherlands, AHN) which is an airborne Aerial Light Detection and Ranging (LIDAR) dataset. Furthermore, satellite imagery will be used to add more information.

4.1 AHN4

AHN is obtained via laser altimetry from aircraft flown over the Netherlands during the winter season. AHN4 is the most recent and airborne LiDAR data of the Netherlands and was recorded between 2020 and 2022 in different regions across the Netherlands, Table 4.1. The flights take several weeks to complete one section. This is due to weather conditions and containing flying permits.

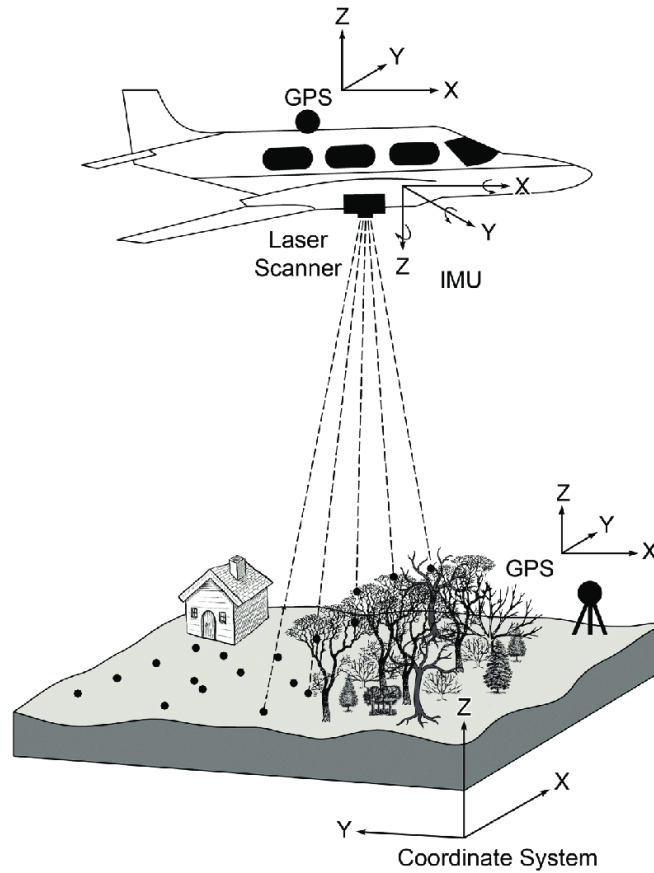


Figure 4.1: General setup of airborne LiDAR systems ([Roman & Ursu, 2016](#))

The laser scanner mounted on the plane and emits a short pulse of an electromagnetic radiation from a transmitter which is then reflected when it hits an object and the time is recorded when the pulse is received back at the scanner receiver 4.1. The range R between the scanner and the object can be calculated with the recorded time traveled t and the speed of light c .

	Metric	AHN 1	AHN 2	AHN 3	AHN 4
Acquisition		1996-2004	2007-2012	2014-2019	2020-2022
Point Density	pts/m ²	1	8-20	8-20	8-20
Accuracy	[m]	0.05	0.05	0.05	0.05
Precision	st.dev. in [m]	0.15	0.05	0.05	0.05

Table 4.1: Data description of the Dutch National Laser Archive ([AHN](#), [n.d.](#))

$$R = \frac{ct}{2} \quad (2)$$

Once the LiDAR data is collected the data is pre-processed by AHN. First it is processed by using the flight data such as Inertial Measurement Unit (IMU) and Global Positioning Service (GPS), see in Figure 4.1. This information is crucial to know the location and orientation of the scanner to accurately determine where the scanned objects are. Then a strip alignment is performed. Strip alignment in airborne LiDAR refers to the process of adjusting overlapping LiDAR data strips from each flight path to correct for vertical and horizontal discrepancies that result from instrument errors or uncertainties in the GPS/INS. These discrepancies can be corrected through a procedure known as strip adjustment, which often involves data-driven methods like least squares surface matching (LSSM) or least z-difference algorithm (LZD) ([L. Wang et al., 2010](#)). Furthermore the data is classified into seven categories such as: Never classified, Unclassified, Ground, Buildings, Water, High tension, and Civil Structures, Tabel 4.2. The class unclassified includes all objects that do not fall under the other categories and include points belonging to vegetation, street furniture, vehicles, containers, etc. A Digital Terrain Model (DTM) and Digital Surface Model (DSM) is also created. The altitude accuracy has a systematic error of 5cm, Stochastic error of 5cm and a vertical error of 95.4% of all points is 15cm ([AHN](#), [n.d.](#)). The point characteristics are the location (x, y, z) , intensity, class, flight lane number, time, number of returns, return number per point. The intensity I of a point is a measure of the return strength of the laser signal, which can indicate the reflectivity of the surface at that point.

$$I = k \cdot \log(R) + C \quad (3)$$

R is the reflectance, k is a system-specific constant, and C is a calibration constant, reflects the return strength of the laser pulse and is indicative of the surface's reflectivity. Other significant attributes are the total number of returns for a single laser pulse, and the return number for this point, specifying its sequence among multiple returns ([ESRI, 2021](#)). The number of returns indicates how many reflections were detected by the LiDAR system for a single laser pulse and the return number specifies the order of this particular return for a given pulse, see Figure 4.2 ([ESRI, 2021](#)). The first return represents the uppermost surfaces in a landscape. The laser pulse can pass through canopy gaps and reflect off intermediate surfaces before reaching the ground.

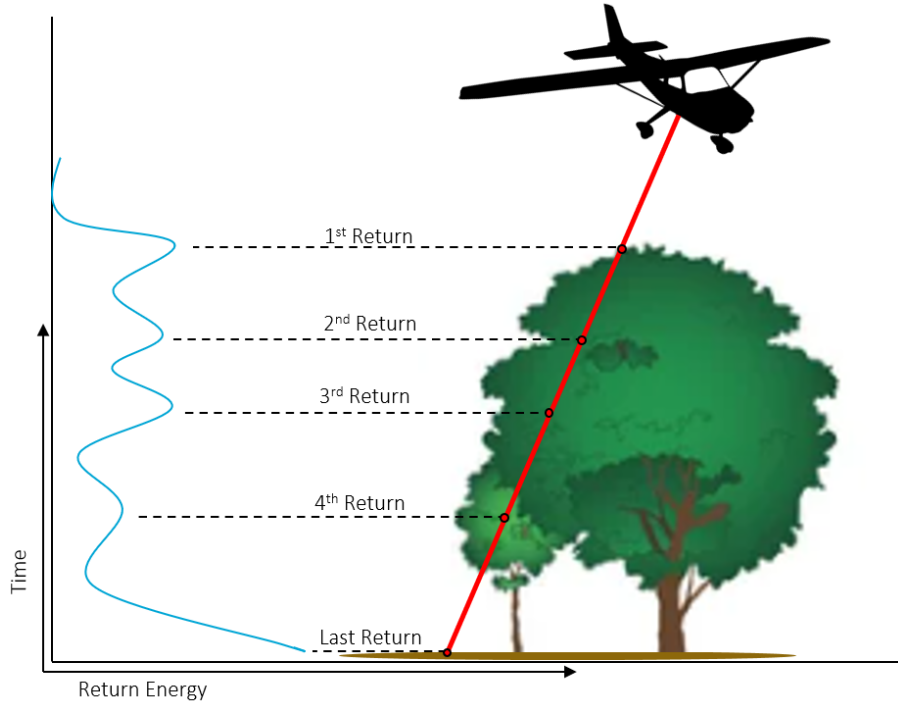


Figure 4.2: Airborne LiDAR system receiving five return values from a single emitted pulse.

Table 4.2: Class Definitions based from AHN

Class	Label	Description
0	Never Classified	Undefined classification
1	Unclassified	Unassigned label
2	Ground	Ground terrain
6	Buildings	Structures
9	Water	Water bodies
14	High Tension	High-tension areas
26	Civil Structure	Man-made structures

The AHN data was colorized using orthophotos from aerial imagery, with a ground sampling distance of 25 cm ([GeoTiles](#), n.d.). The AHN data is also tiled into 1 x 1.25km tiles, see one tile example in Figure 4.3. This tile has 45,326,111 number of points recorded which were classified, see Table 4.3. While AHN provides a great amount of information. The combination of multiple observations could further improve the tree characteristic analysis, since the AHN data is collected during leave-off season. It would be beneficial to add information about the seasonal change. This can hopefully be achieved by adding imagery.



Figure 4.3: AHN4 data in RGB based from aerial imagery of a tile (37EN1) 1x1.25km in Delft



Figure 4.4: AHN classified tile (37EN1) 1x1.25km in Delft with classes based on Table 4.3

Class Name	Number of Points	Class Number
Unclassified	7,849,626	1
Ground	20,883,436	2
Building	16,037,536	6
Water	222,817	9
Civil Structure	332,696	26

Table 4.3: Point classification summary for tile sub-tiles 37EN1

4.2 Aerial Imagery

The Netherlands Space Office (NSO) provides yearly aerial images of the Netherlands from 2016 to 2023 which were obtained using aeroplanes. They have a higher resolution than the satellite imagery.

While this data has a very high resolution, with a recent resolution of 7.5cm from 2021 and a prior resolution of 25cm, it will not be used in this research due to its temporal resolution. The aerial images are captured during one time frame and do not show seasonal variability, see Figure 4.5. However, they are captured during almost perfect conditions. This means that shadowing effect is low and the weather is so that visibility is granted. Nonetheless, for RGB and NIR tree features of different seasons, the aerial imagery is not usable. This is why the focus will lie with spectral satellite data.

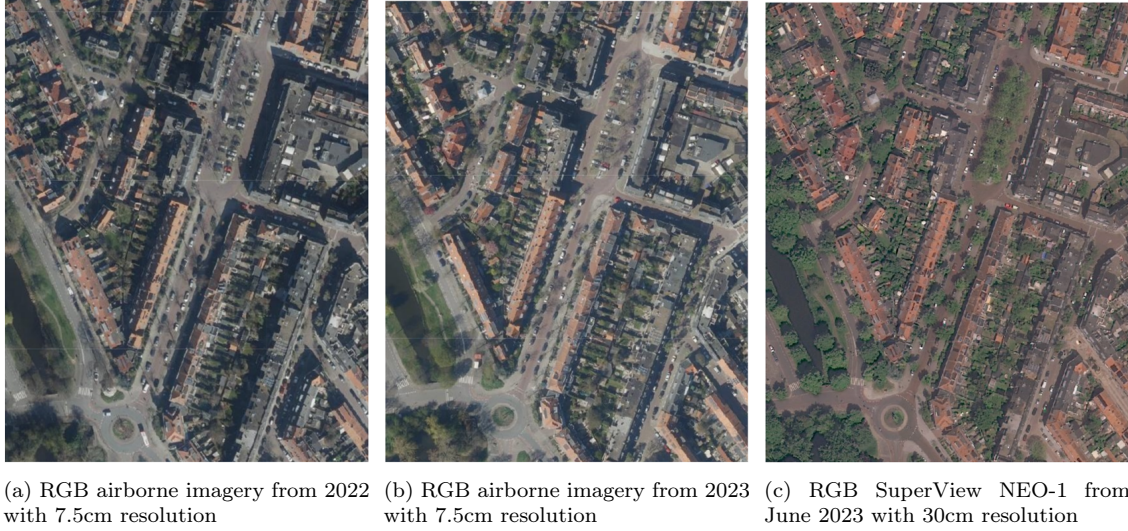


Figure 4.5: Airborne imagery vs satellite imagery in Delft

The colored AHN4 data seen in the report is based on the airborne imagery. These colors will not be used for the later classification of trees and is mainly a tool for visualization of the dataset, see example in Appendix A3 and A4.

4.3 Spectral Satellite Imagery

The Netherlands Space Office (NSO) provides high-resolution satellite imagery of the Netherlands, initially collected by SuperView-1 and -2 satellites from 2019 to 2022, with a resolution of 50 cm. In 2023, the SuperView NEO satellites began collecting even higher resolution data at 30 cm. These satellites capture four spectral bands: blue, green, red, and near-infrared (NIR).



Figure 4.6: SuperView-1 high resolution satellite imagery of the Paardenmarkt in Delft during different seasons of 2023 with 30cm resolution

The NSO details the preprocessing steps for satellite images. Initially, the raw images undergo radiometric calibration to correct sensor data. Following this, sensor correction is applied to address any distortions or inaccuracies (NSO, n.d.). The final step is orthorectification, which aligns the images accurately with the Earth’s surface, ensuring geometric precision (NSO, n.d.). The satellites provide imagery of the Netherlands throughout the different seasons, see Figure 4.6.

4.4 Delft Urban Tree Data

In Delft the municipality maintains a tree inventory. The inventory consists of the trees managed in Delft by the municipality. The database includes the trees location, species and plantation time. Furthermore, it includes other tree characteristics such as a tree height and diameter. However, these are usually provided in ranges and only differentiate tree heights and diameters based on 5m differences. This information is also not included for each entry and it is unknown when they were added to the database. The database has a record of 35467 trees, 389 different tree species and was published in 2022 and was updated in February 2023 (Gemeente Delft, 2024). The data consist of the tree species, see histogram in Figure 4.8, and their location as well as other factors such as tree height (Figure 4.7), tree age (Figure A2), and management, further described in Appendix A.2.

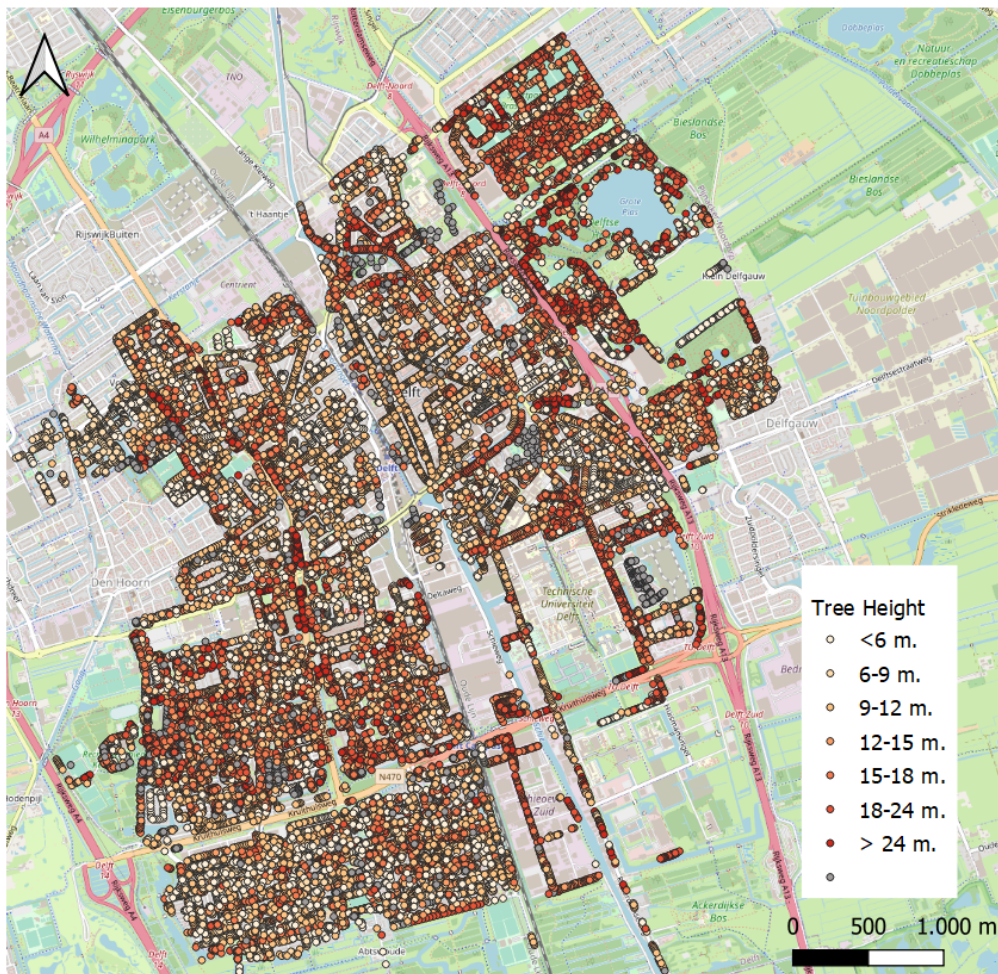


Figure 4.7: Map of tree heights from the Delft Municipality Tree Inventory

The trees documented by the Delft municipality are also managed which means they are occasionally cut and when young they are corrected to grow straight. This can make them appear different than free growing trees. Tree management includes the cutting of branches that endanger the surrounding structures. Tree branches are also inspected or cut when showing weakness to prevent them from falling.

The inventory has some limitations. While it provides many attributes for each tree, the attributes significant is not provided, thereby making the interpretation difficult. Furthermore, the inventory is updated but it is unknown if the entire tree inventory is reevaluated or only new trees are added etc.

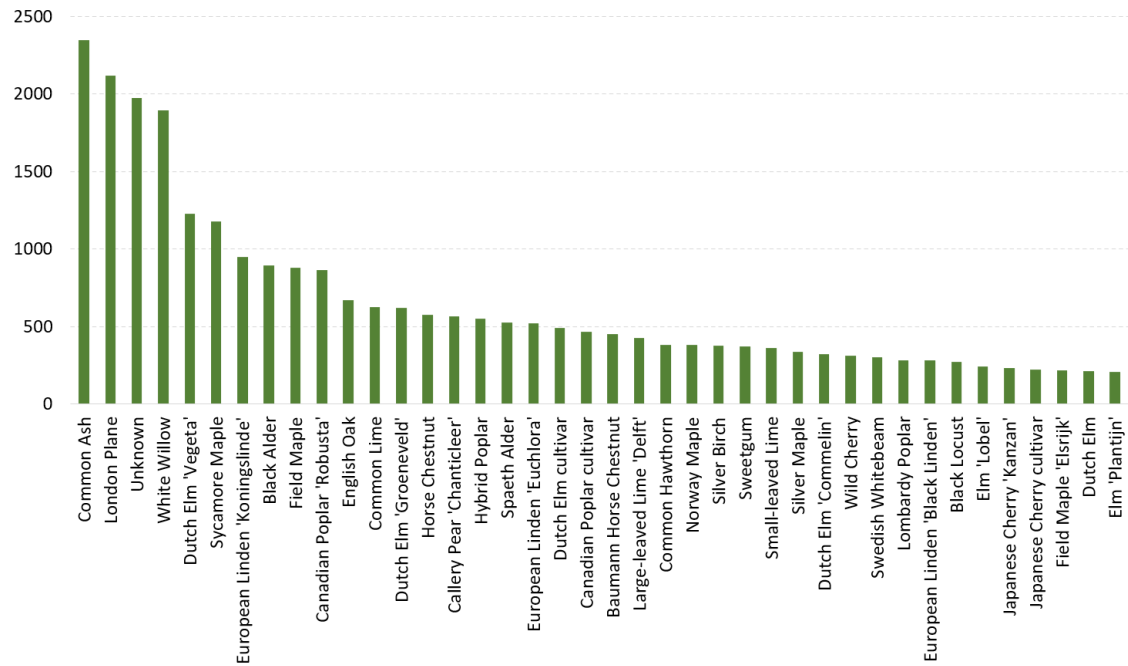


Figure 4.8: Histogram of tree species with count larger than 200 from Delft Municipality Tree Inventory. The common names of the tree species are derived from the scientific names in the dutch Delft Municipality Inventory, see Appendix A.3 for original scientific names

5 Methodology

To get to the goal of classifying urban tree characteristics from LiDAR and high resolution imagery using machine learning methods the workflow can be subdivided into four steps, listed below and shown in Figure 5.1.

1. **Tree Segmentation from the LiDAR data:** Extracting all tree points from AHN4
 - (a) Pre-Processing: Remove noise and irrelevant points, classes from the point cloud. Compute point height from ground and remove points below 2m.
 - (b) Tree Classification using machine learning method, Random Forest Classification: Using a training dataset run a Random Forest classification model to find tree points.
 - (c) Tree Segmentation using Geometric Features: Computing different geometric features and filter the dataset to extract tree points.
 - (d) Validation: Using a testing dataset to evaluate tree segmentation results.
2. **Individual Tree Detection:** Finding individual tree locations.
 - (a) Applying "Point-based Individual Tree Delineation from 3D LiDAR Point Cloud Data"
 - (b) Validation: Using the Delft Municipality Tree Inventory from the results are evaluated. Additionally, case studies are conducted to further evaluate the achievements and limitations of the method.
3. **Feature Extraction:** Extract tree features from AHN4 and the spectral images.
 - (a) Extract reflectance features from AHN4
 - (b) Extract geometric features from AHN4
 - (c) Extract spectral features from satellite images
4. **Unsupervised clustering:**
 - (a) K-means: creating k-clusters in which each tree is grouped based on nearest mean
 - (b) Validation: Different feature input result in different tree clusters. The features driving the different results are evaluated. To evaluate the clustering outcome the results are compared to the tree species recorded in the Delft Municipality Tree Inventory. The evaluation will focus on how this clustering provides different information compared to the tree species.

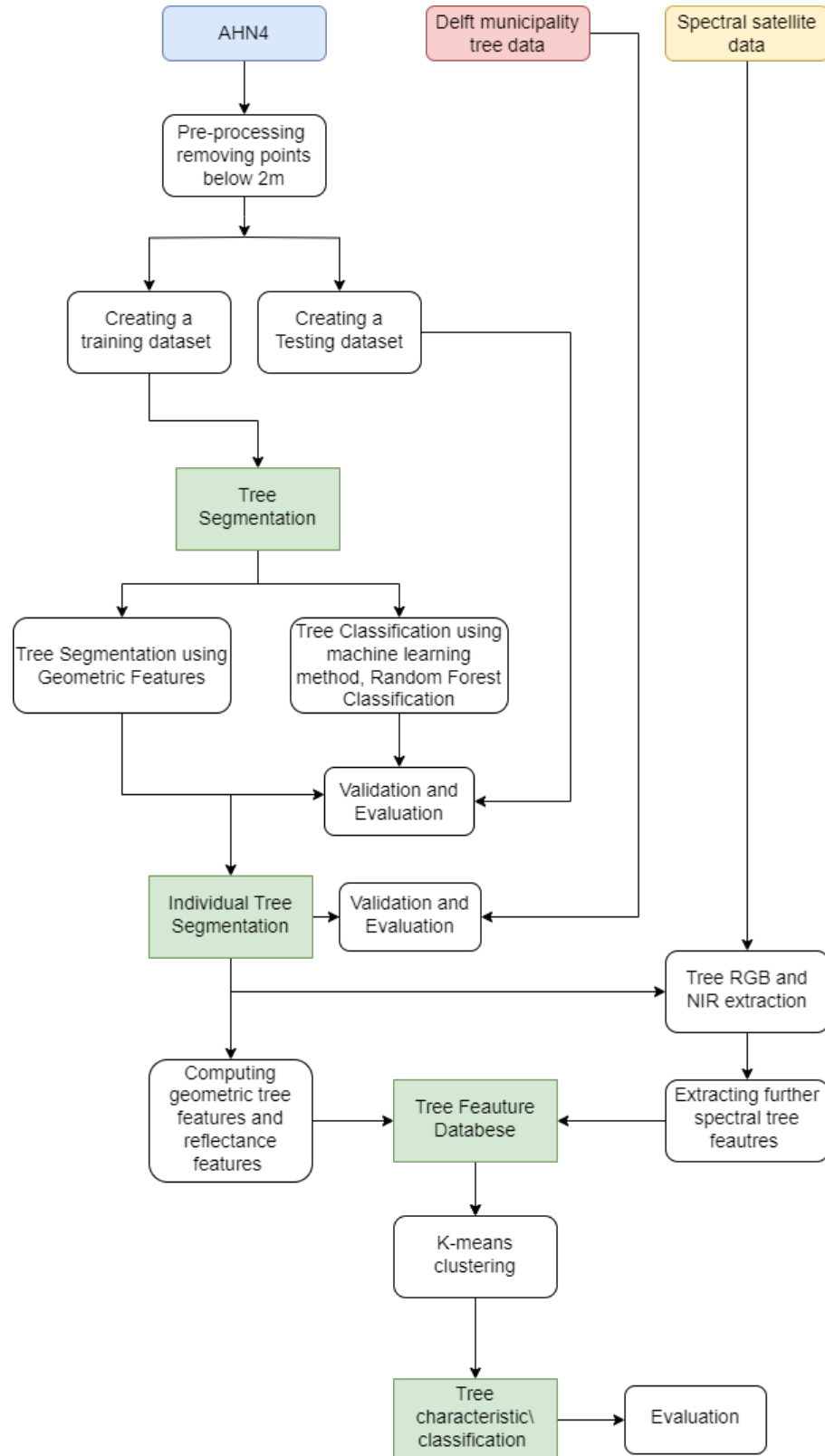


Figure 5.1: Methodology flowchart

5.1 Tree Segmentation From the Airborne LiDAR Data

To extract tree points from the AHN4 LiDAR data, the following steps are undertaken:

1. Pre-processing:
 - (a) Point filtering: Points classified by AHN4 as not vegetation are filtered out.
 - (b) A ground mesh is created: this is done by subsampling the points classified as ground points by AHN4.
 - (c) Height-based filtering: The height to ground is computed for all potential tree points and points below 2m are filtered.
2. Tree segmentation: two different methods are implemented to extract tree points:
 - (a) Tree segmentation using supervised machine learning: Random Forest classification.
 - (b) Tree segmentation using geometric features.

5.1.1 Pre-processing of AHN4

To extract tree points from an original 1x 1.25km AHN4 tile with various classes, a series of preprocessing steps are undertaken to refine the data. The original tile comprises of different classes, where each class represents a specific land cover type. These classifications have been done by AHN. The classes are defined as follows: 0=never classified, 1=unclassified, 2=ground, 6=buildings, 9=water, 14=high tension, and 26=civil structure, Table 4.2.

The first step is to isolate the ground, which is represented by class 2. This involves extracting and subsampling the points labeled as class 2 with a minimum distance of 5 meters between points. Subsampling helps to reduce the density of points, making subsequent processing more efficient, Figure 5.3. The result is a refined set of ground points that captures the topography of the terrain.

Next, a mesh is created using triangulation based on the selected ground points. This is done by using in CloudCompare the Delaunay 2.5D (best fitting plane) computation, see steps in Figure 5.2 and results for the total tile in Figure 5.4. Triangulation forms a mesh by connecting adjacent points with triangles, providing a continuous representation of the ground surface.

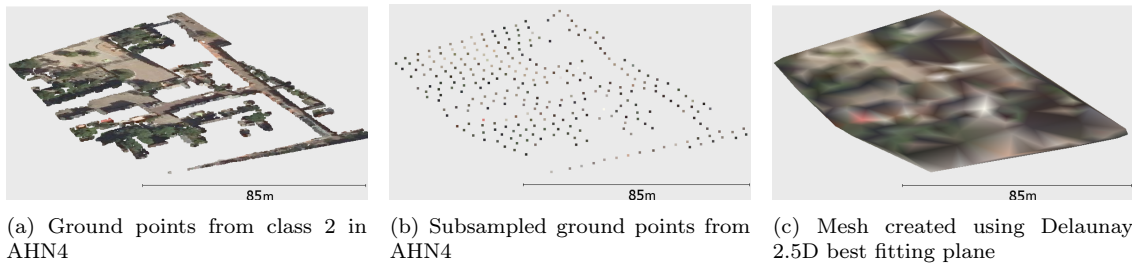


Figure 5.2: Example of ground mesh creation. Note the colors are from the aerial imagery and the ground points are often colored by objects above the ground.



Figure 5.3: AHN4 class 2 ground points subsampled with a min distance of 5m



Figure 5.4: Intensity mesh of AHN4 class 2 ground points subsampled with a min distance of 5m

Subsequently, points labeled as class 1 are extracted from the original data. This class, representing unclassified points, is representing the above ground vegetation as well as street furniture and other objects in the data. A distance computation between point cloud to mesh is then performed using CloudCompare, Figure 5.5. This will result in a height map of the unclassified points with reference to the ground in that area, Figure 5.6.

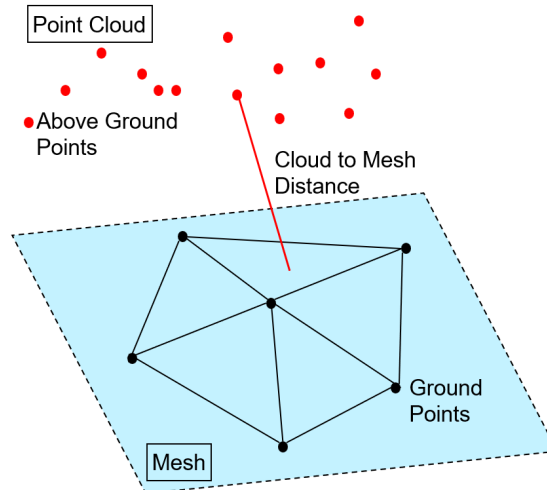


Figure 5.5: Cloud to mesh computation

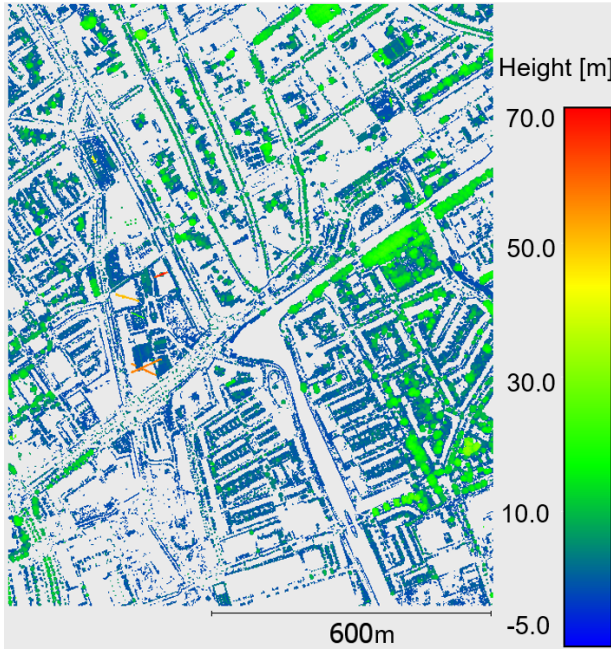


Figure 5.6: Cloud to mesh distance computation. Point height relative to computed ground mesh.

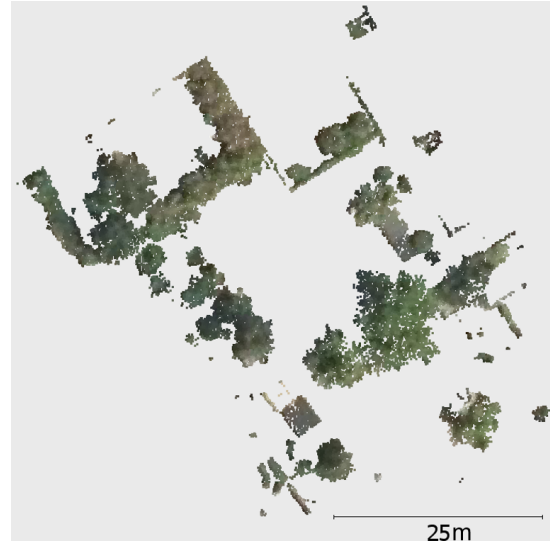


Figure 5.7: AHN4 class 1 in RGB after filtering points by 2 ground height

To identify and isolate trees, a height criterion is applied. It is assumed that tree crowns are above 2 meters. Consequently, all points below this height are removed from the point cloud, see Figure 5.7 for total tile and see Figure 5.8 and 5.9 for close up filtering. This step helps filter out irrelevant points, focusing the analysis specifically on the tree canopy.



(a) Top view AHN4 class 1 points before height-based filtering



(b) Top view AHN4 class 1 points after height-based filtering

Figure 5.8: Top view comparison of AHN4 class 1 points before and after height-based filtering.

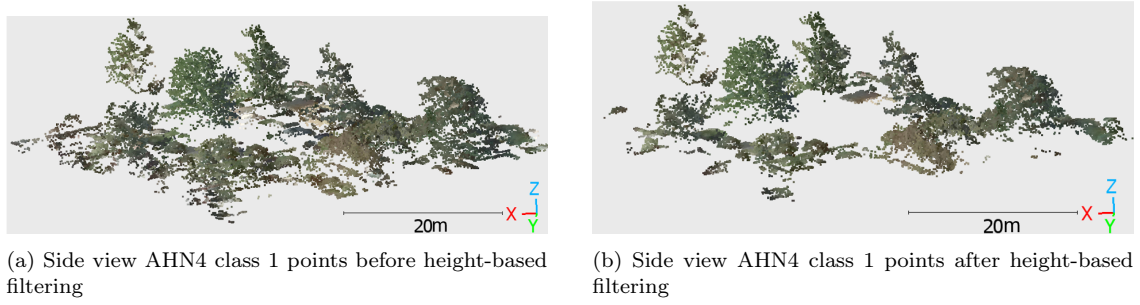


Figure 5.9: Side view comparison of AHN4 class 1 points before and after height-based filtering.

5.1.2 Tree Classification Using Machine Learning

The first method to identify the tree points is by using supervised machine learning. For the supervised classification a training dataset is created. This is done by manually selecting tree points and non tree points and assigning a label. One AHN4 tile of 1 x 1.25 km is used for the original training data. Using the Delft municipality data a variate of different tree species and ages is selected as training data. The training data will then consist of two classes of points: tree points and non-tree points. The training data is then used with a supervised classification method, in this case the Random Forrest (RF) classifier, to analyze the rest of the tile. Based on past research this is a sufficient method to classify urban trees from LiDAR data. Although the quality is dependent on the training data this has been done before and and other research has created their own multiple training datasets. The training dataset was created manually from a 1x1.25 km tile, with an initial preprocessing step to filter out points below 2 meters in height. This refined dataset comprises 5,580,334 points identified as trees and 317,194 points categorized as non-tree entities.

The Random Forest Model created uses the following parameters and values seen in table 5.1:

Parameter	Value	Description
n_estimators	500	This parameter specifies the number of trees in the forest. A higher number typically improves model performance but also increases computational complexity and time.
min_samples_split	10	This parameter sets the minimum number of samples required to split an internal node. Higher values prevent the creation of nodes that contain too few samples, which can help mitigate overfitting.
min_samples_leaf	15	This parameter determines the minimum number of samples required to be at a leaf node. Setting this value higher can smooth the model, especially for regression.
probability	0.80	This parameter specifies the cutoff threshold for the probability of a prediction required to classify a data point into a specific class. If the predicted probability for any class is below this threshold, the data point is classified as belonging to an 'unknown' class.

Table 5.1: Input parameters for Random Forest model

An example of a tree created in the RF model is shown in image 5.10.

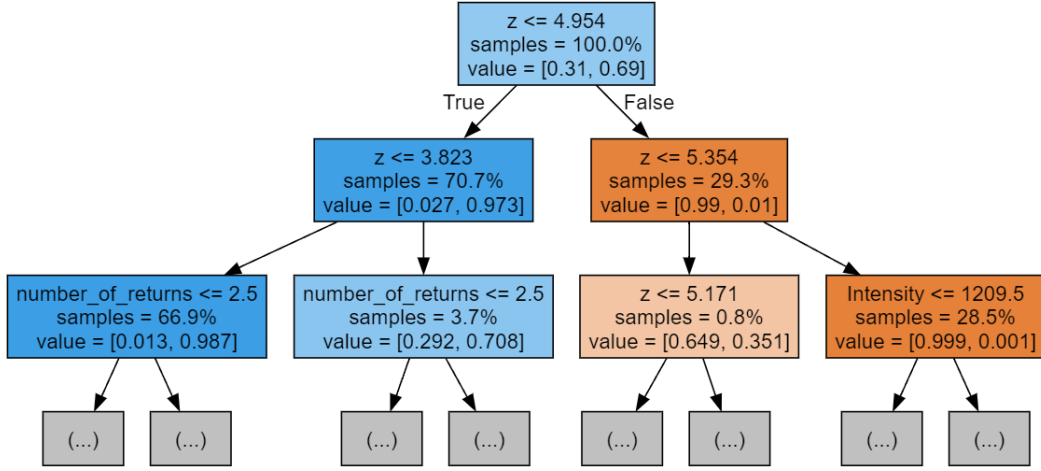


Figure 5.10: Example tree showing Random Forest classification model

5.1.2.1 Computational Complexity of Random Forest Classification

The processing time for the Random Forest classification is separated into two steps: 1) building the RF model and 2) running the RF model. Building the RF model depends on the number of samples in the training data (n) and the number of features (m). Assuming the average depth of a decision tree being $\log(m)$ and if the model consist of k trees, the time complexity of building the RF model is:

$$O(k * n * m * \log(m)) \quad (4)$$

The time complexity can be reduced by restricting the maximum depth of the tree to be d . Then time complexity is:

$$O(k * n * m * d) \quad (5)$$

If $m \gg (d, n)$ then the time complexity becomes:

$$O(k * m) \quad (6)$$

Running the RF model is depending on the tree number k and the average depth of the trees $\log(m)$.

$$O(k * \log(m)) \quad (7)$$

5.1.3 Tree Segmentation Using Geometric Features

In the analysis of 3D point cloud data, geometric features such as PCA2, Roughness, Sphericity, and Normal Change Rate play crucial roles in interpreting the structural and textural character-

istics of the scanned objects. First, voxels with a dimension of 2m will be created to structure the point cloud data efficiently. This dimension was chosen based on the data. Since the data includes small structures such as street furniture and bigger structures such as trees and cranes a voxel size was chosen that can distinguish these structures. The larger the voxel the longer the commutation time. Subsequently, the geometric parameters will be computed within these voxels to extract detailed information about the surface and shape properties of the objects under study. PCA2, for instance, helps in identifying the secondary direction of variance in the data, revealing underlying patterns that might not be apparent from the primary variance direction alone (Lague et al., 2013). Roughness quantifies the surface texture, providing insights into the physical characteristics of the surface. Sphericity measures how closely the shape of an object approximates a sphere, which is crucial for classifying and analyzing spherical features in the data such as trees in contrast to other objects such as tram posts or cranes. Lastly, the Normal Change Rate is instrumental in detecting edges, corners, and areas of high curvature, offering a deeper understanding of the geometric complexity of the scanned objects.

Below is a short list of the parameters and their descriptions:

- **PCA2:** The variance in the direction orthogonal to the primary variance, highlighting secondary structural patterns.
- **Roughness:** A measure of the surface texture, indicating variations in surface normals or distances from a fitted surface.
- **Sphericity:** An assessment of how closely an object's shape resembles a sphere, used for analyzing roundness.
- **Normal Change Rate:** The rate at which the surface normal vector changes, useful for identifying significant geometric features.

PCA2 is derived from the Principal Component Analysis (PCA), where the second principal component (PCA2) is calculated by identifying the eigenvector corresponding to the second largest eigenvalue of the covariance matrix of the point coordinates (Lague et al., 2013). The covariance matrix C is given by:

$$C = \frac{1}{N-1} \sum_{i=1}^N (X_i - \bar{X})(X_i - \bar{X})^T \quad (8)$$

where X_i represents the point coordinates and $\bar{X}$ is the mean coordinate vector.

Roughness measures the deviation of surface points from a fitted plane, often calculated as the standard deviation of the distances (d) of points from the plane:

$$Roughness = \sqrt{\frac{1}{N} \sum_{i=1}^N d_i^2} \quad (9)$$

Sphericity, indicative of how closely an object's shape resembles a sphere, can be quantified by the ratio of the PCA eigenvalues, λ_1 , λ_2 , and λ_3 , where a higher ratio reflects higher sphericity:

$$Sphericity = \frac{\min(\lambda_1, \lambda_2, \lambda_3)}{\max(\lambda_1, \lambda_2, \lambda_3)} \quad (10)$$

The Normal Change Rate, reflecting the rate of change of the surface normal across the surface, can be expressed through the angular difference ($\Delta\theta$) between normals of adjacent points:

$$\text{Normal Change Rate} = \frac{1}{N} \sum_{i=1}^N \Delta\theta_i \quad (11)$$

These parameters, when computed, offer a comprehensive understanding of the scanned surface's geometric and textural properties, facilitating advanced 3D analyses.

5.2 Individual Tree Segmentation Based on Region Growing

Now the tile is classified in three groups: 1. tree points, 2. no tree points, and 3. unclassified. However, to extract the tree geometric features the tree points need to be further segmented into groups of individual trees. This will be done by running an Individual Tree Detection algorithm (ITD) called "Point-based Individual Tree Delineation from 3D LiDAR Point Cloud Data" in C++ (J. Wang, 2017).

First the tree point data is voxelized which means it is sorted into cubic cells. Then a clustering is performed to find connecting filled voxels to find clusters of trees. This is done to reduce computation time by later only looking to separate trees within these clusters. In those clusters the tree tops are located as seed points, see Figure 5.11. These initial seed points are based on the condition that they are the top cell with no filled cell above but has cells below.

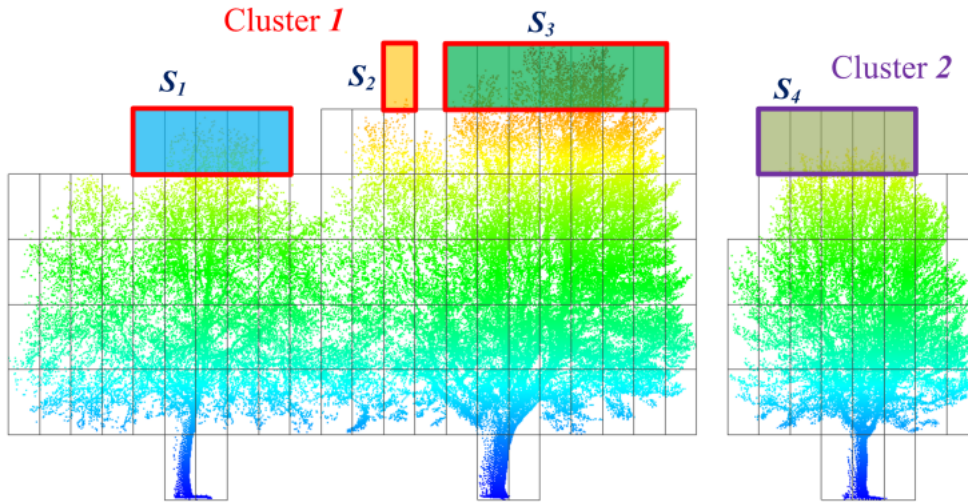


Figure 5.11: "Connected cells are clustered as potential seeds of individual trees from the top layer downwards. S1, S2 and S3 are potential seeds of Cluster 1 and S4 of Cluster 2" (J. Wang, 2017)

When multiple seed points are located in one cluster it means there is a likelihood of multiple trees being present. However, it can also indicate a tree that has a crown with multiple high branches like shown in Figure 5.11 where S2 and S3 belong to the same tree. To eliminate, this a parameter is set that gives the minimum distance between two seed points.

Once the tree top seed points have been located they are labeled with a tree ID. Unassigned voxels are then labeled based on a connectivity coefficient. First the cells connected below the seed points

are labeled as the same tree as the seed point voxel. Then neighboring voxels are evaluated by computing a prediction how likely the voxel is to belong to which seed point.

Depending on the voxel size the computation time varies but so does the results. With smaller voxels the prediction of point labels where trees are intertwined are much more accurate. However smaller voxels can also lead to more seed point identification. The tree segmentation code is dependent on three main parameters which can be adjusted depending on the dataset, Table 5.2. The point density also plays a role in the accurate determination of the tree separation.

Parameter	Value	Description
radius	1.5	The radius is the search radius in meters. It should be adjusted according to the average point density to ensure there are a certain number of points within the radius.
verticalResolution	1.0	The vertical resolution in meters of the layers depends on the overall point density and fineness of the admired results.
miniPtsPerCluster	10	Minimum number of points per cluster. This will remove small point clusters.

Table 5.2: Input Parameters for "Point-based Individual Tree Delineation from 3D LiDAR Point Cloud Data" (J. Wang, 2018)

5.3 Tree Features

The next step in the methodology is to extract valuable tree features from the LiDAR and satellite data to create a database with geometric, reflectance and spectral features for the individual trees.

5.3.1 High Spectral Image Features

The trees in Delft are mostly deciduous trees which means during the winter seasons they shed their leaves. The trees change considerably during seasons. While in winter they are without leaves some trees grow flower buds and/or leave buds in spring time. Once leaves start developing they usually look lighter in color and more vibrant compared to the deep darker hues the summer canopy has. During fall the leaves start to die and shed and the canopy will thin out and get more dry and loose its green color and start to go from yellow to brown. These changes in the leaves are also seen in the Normalized Difference Vegetation Index (NDVI). In spring the leaves are developing and begin to expand and gain in length and width this increases the NDVI. In fall the opposite occurs and the NDVI starts to decrease (Yang et al., 2017). The growing periods and speed vary between trees species. Other factors also play a role in the tree development such as water access, tree health and age.

The 2D tree center points are located by finding the mean x, y coordinates of each point group with the same tree label. After the mosaics are geo-referenced to the same reference system as the AHN4 the pixel information near the tree center points can be extracted. This can also be used to validate tree locations by checking if the pixels are green near the tree center point. However, that does not always hold true as some trees are naturally differently colored. High spectral (MS) images provide a rich source of data for assessing vegetation health through spectral signatures.

The seasonal RGB and NIR is extracted from the images. The extraction of Red and Near-Infrared (NIR) bands allows for the computation of the NDVI, a crucial indicator of vegetative vigor.

By having the data in the same reference system their overlap can be found. To find the best valuable spectral information for each tree the mean and center pixels of the individual trees of the mosaics will be used. The tree center locations are detected and the RGB and NDVI values are extracted. Since the tree crowns do not have a uniform color due to different growth and shadows a box around the center is generated and the mean RGB value is taken from within the box, Figure 5.12. This will also mean that pixels at the edges of the tree crown will not be used. This is done to avoid pixels that have input of the tree crown and what lays below.



Figure 5.12: Spectral data extraction for tree location. The tree location is marked in red, and the mean RGB values are extracted within the yellow box, 0.9x0.9cm (Note that the axis is in pixel number, where one pixel is 0.3x0.3 cm).

The box is 3x3 pixel big which is 0.9mx0.9m. This size is chosen since small trees are within that size and the mean value still give enough insight into the color variation.

Multiple images from different seasons are used to extract the RGB and NIR. This will give information about the color changes between spring, summer, and fall. Since no leaves will be visible in winter and it is unlikely that the pixels will represent valuable tree information and will be influenced by the ground, winter images will not be used. Past research shows that late spring imagery is very valuable when trying to classify trees from mosaics (Schenk & Csathó, 2002; Pu et al., 2018). Therefore, images from spring summer and fall are used from SuperView NEO-1 with a resolution of 30cm are used to extract the data, Table 5.3. All extracted spectral images are have four bands and are orthorectified.

Date	Mosaic
04-05-2023	Spring spectral mosaic with 30cm resolution
06-06-2023	Late Spring spectral mosaic with 30cm resolution
12-08-2023	Summer spectral mosaic with 30cm resolution
17-10-2023	Fall spectral mosaic with 30cm resolution

Table 5.3: Spectral images selected for feature extraction

5.3.2 LiDAR Data Features

LiDAR data facilitates the extraction of detailed three-dimensional structural features of vegetation. Distinctive geometrical properties are derived from the point clouds, which include the shape and spread of tree crowns, as well as the density and distribution of foliage.

- **Tree Height:** The vertical extent of the tree is determined by identifying the highest point in the point cloud data, which provides a measure of the tree’s height. The tree height distribution is also evaluated by computing the height kurtosis and 25% and 75% percentile.
- **Crown Dimensions:** By analyzing the spread of the point cloud horizontally, the maximum and minimum crown diameters at median height are computed. These measurements capture the extent of the crown and provide insights into the tree’s growth patterns.
- **Crown Density:** The number of points within the tree crown gives an estimate of the foliage density, which is indicative of the crown’s health and thickness. The crown density is evaluated by computing the mean distance between points and the point counts.
- **Sphericity:** Through mathematical modeling, fitting an ellipsoid to the 3D points using least squares, the sphericity of the crown is estimated. This sphericity index evaluates the roundness of the tree crown, which can be indicative of certain species or health conditions.

The features extracted from the airborne LiDAR data AHN4 (ALS) and the multispectral images (MS) will be assigned to each tree center location. These features are labeled as described in Table 5.4.

No.	Label	Feature Name	Source
1.	i_max	Maximum intensity	ALS
2.	i_med	Median intensity	ALS
3.	i_min	Minimum intensity	ALS
4.	i_kurt	Intensity kurtosis	ALS
5.	i_q75	75% percentile of intensity	ALS
6.	i_q25	25% percentile of intensity	ALS
7.	i_var	Variance of intensity	ALS
8.	z_max	Maximum height	ALS
9.	z_min	Minimum Height	ALS
10.	z_med	Median height	ALS
11.	z_kurt	Height kurtosis	ALS
12.	z_q75	75% percentile of height	ALS
13.	z_q25	25% percentile of height	ALS
14.	z_var	Variance of height	ALS
15.	NoR_max	Maximum of number of returns	ALS
16.	NoR_med	Median of number of returns	ALS
17.	NoR_min	Minimum of number of returns	ALS
18.	NoR_kurt	Kurtosis of number of returns	ALS
19.	NoR_q75	75% percentile of number of returns	ALS
20.	NoR_q25	25% percentile of number of returns	ALS
21.	NoR_var	Variance in number of returns	ALS
22.	sph	Sphericity	ALS
23.	d_max	Maximum diameter at median height	ALS
24.	d_min	Minimum diameter at median height	ALS
25.	dist_mean	Mean Distance between points	ALS
26.	point_count	Count of points	ALS
27.	RGB_spring	RGB median value form spring image (04-05-2023)	MS
28.	RGB_latespring	RGB median value form late spring image (06-06-2023)	MS
29.	RGB_summer	RGB median value from summer image (12-08-2023)	MS
30.	RGB_fall	RGB median value from fall image (17-10-2023)	MS
31.	NIR_spring	NIR median value form spring image (04-05-2023)	MS
32.	NIR_latespring	NIR median value form late spring image (06-06-2023)	MS
33.	NIR_summer	NIR median value form summer image (12-08-2023)	MS
34.	NIR_fall	NIR median value form fall image (17-10-2023)	MS
35.	NDVI_spring	NDVI median value form spring image (04-05-2023)	MS
36.	NDVI_latespring	NDVI median value form late spring image (06-06-2023)	MS
37.	NDVI_summer	NDVI median value form summer image (12-08-2023)	MS
38.	NDVI_var_fall	NDVI variance value form fall image (17-10-2023)	MS
39.	NDVI_var_spring	NDVI variance value form spring image (04-05-2023)	MS
40.	NDVI_var_latespring	NDVI variance value form late spring image (06-06-2023)	MS
41.	NDVI_var_summer	NDVI variance value form summer image (12-08-2023)	MS
42.	NDVI_var_fall	NDVI variance value form fall image (17-10-2023)	MS
43.	NDVI_25_spring	25% percentile of NDVI value form spring image (04-05-2023)	MS
44.	NDVI_25_latespring	25% percentile of NDVI value form late spring image (06-06-2023)	MS
45.	NDVI_25_summer	25% percentile of NDVI value form summer image (12-08-2023)	MS
46.	NDVI_25_fall	25% percentile of NDVI value form fall image (17-10-2023)	MS
47.	NDVI_75_spring	75% percentile of NDVI value form spring image (04-05-2023)	MS
48.	NDVI_75_latespring	75% percentile of NDVI value form late spring image (06-06-2023)	MS
49.	NDVI_75_summer	75% percentile of NDVI value form summer image (12-08-2023)	MS
50.	NDVI_75_fall	75% percentile of NDVI value form fall image (17-10-2023)	MS

Table 5.4: Tree features extracted from AHN4 and the spectral data MS.

5.4 Clustering

A clustering algorithm is run on the data including the tree features. Clustering is an unsupervised learning method that groups a collection of unlabeled objects (Chaovalitwongse et al., 2009). K-Means is a popular method for clustering where the number of clusters (k) is predetermined. It's simple and efficient but requires specifying the number of clusters in advance.

Based on the Delft Municipality Tree Inventory it is known that there are around 389 different tree species in Delft of which 40 have more than 200 trees in Delft. By only considering the main Latin name of the species the species can be grouped further reducing the total different species to 73 tree groups of which 22 have more then 200 trees in Delft. This is a reasonable number to create clusters. In the study area selected the Delft Tree Inventory shows 61 different tree species. The clustering group is first selected to be k=30 to determine the output and then is further decreased to k=15 and k=8. While tree species is an important indication of different tree characteristics the main goal is to group trees based on their ALS and MS characteristics.

By selecting different tree features as input for the clustering their importance and impact on the results can be evaluated. Three main situations are evaluated:

1. ALS and MS tree features
2. ALS tree features
3. MS tree features

5.4.1 Computational Complexity of K-means Clustering

The k-means clustering time complexity is in the average case:

$$O(i * n * (d * k + 1)) \quad (12)$$

and in the best case:

$$O(n * d * k * i) \quad (13)$$

where n is the number of observations, k is the overall number of clusters, d is the number of features, and i is the number of iterations.

5.5 Validation and Method Evaluation

Throughout the tree classification steps different methods to evaluate the results are applied. First the tree segmentation from LiDAR data is evaluated. Two methods were applied: first Random Forest classification, second segmentation using geometric features. The RF classification can be validated by evaluating the model performance on a testing dataset. This testing dataset is manually created. The tree segmentation based on geometric feature can also be evaluated using the testing dataset. Furthermore, both results can be visually inspected to analyze areas where the algorithm shows confident results and where issues can be noticed.

The next step in this methodology is the Individual Tree Detection. Furthermore, the median location of the detected trees in the study area is extracted. The location of municipality trees can be extracted from the Delft Municipality Tree Inventory. While the algorithm also includes

privately owned trees a validation of true positives can be made. In addition, the distance between estimated tree location and "true" tree location based on the municipality tree data can be calculated. However, this validation is based on the assumptions that the Delft Municipality Tree Inventory is accurate.

The Delft Municipality Tree Inventory describes some tree features such as tree height and age. The tree maximum height is a feature extracted from the LiDAR data and can be compared to the recorded tree heights.

Using the Delft Municipality Tree Inventory, the performance of K-means clustering on various tree species can be evaluated. The clustering results are validated visually by examining the data and conducting fieldwork in specific areas. Instead of focusing solely on method validation, this evaluation assesses the performance through manual visual analysis and field observations. The analysis explores different aspects of the clustering results, highlighting their achievements and limitations. This comprehensive approach ensures a thorough understanding of the outcomes and their implications.

6 Results

This chapter presents the results of the study. First, the evaluation begins with the tree classification using Random Forest classification, comparing these results with tree segmentation based on geometric features. Following this, an analysis of the Individual Tree Detection (ITD) method is conducted through multiple case studies to assess its achievements and limitations. The study then examines the extracted tree features from LiDAR, such as tree height, crown sphericity, and other geometric characteristics, alongside satellite imagery features like RGB and NIR, focusing on their seasonal and temporal changes. The clustering results are subsequently evaluated, discussing their achievements and limitations with case study examples. Finally, the processing efficiency and scalability of the methods employed in this study are analyzed.

6.1 Random Forest Tree Classification

The Random Forest classification was executed, using the parameters described in Table 5.1. Upon completion of the classification process, the dataset was classified into three distinct classes: 'tree' [0], 'non-tree' [1], and 'unclassified' [2]. The distribution of these classifications is visually represented in both a histogram and a corresponding image, as depicted in Figure 6.1 and 6.2.

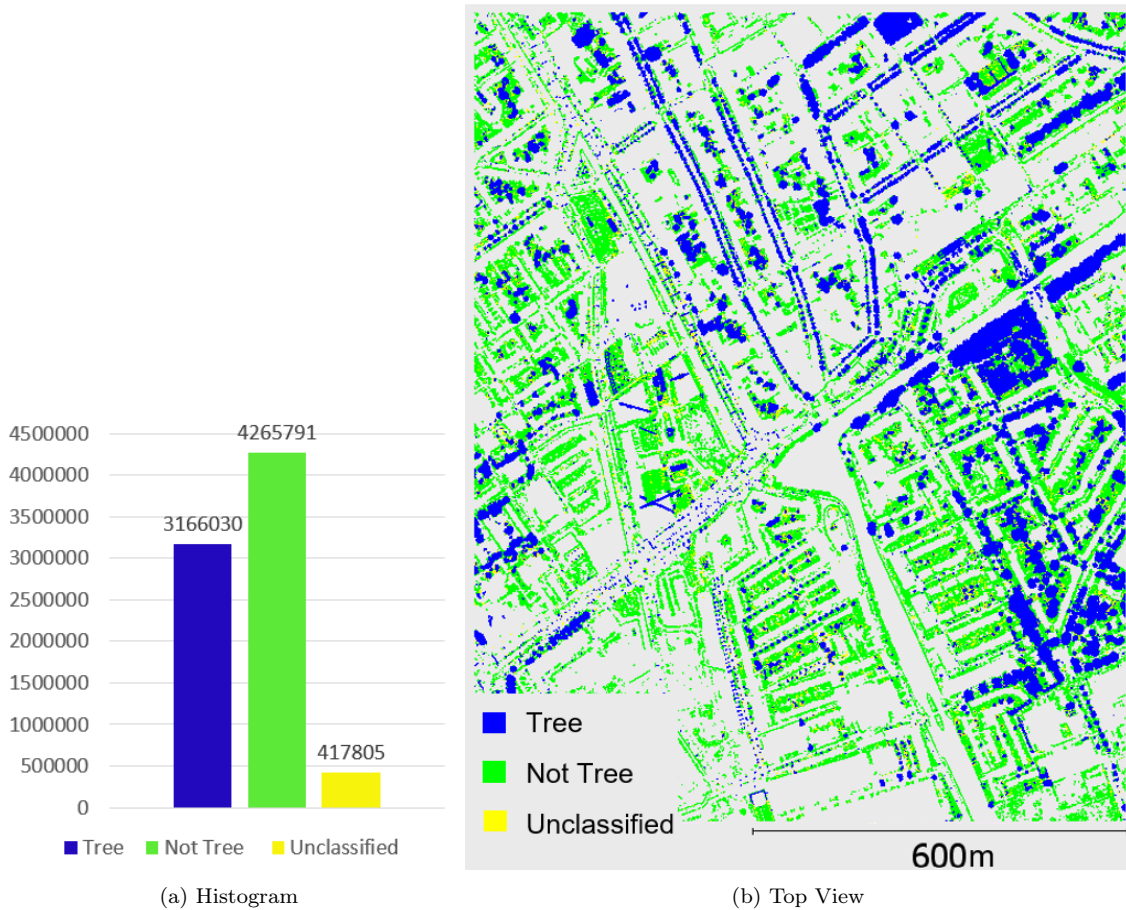


Figure 6.1: Histogram and top view of RF classified points, Tile 37EN1_15. A more detailed visualization of the RF results can be found in the appendix, see Figure A6.

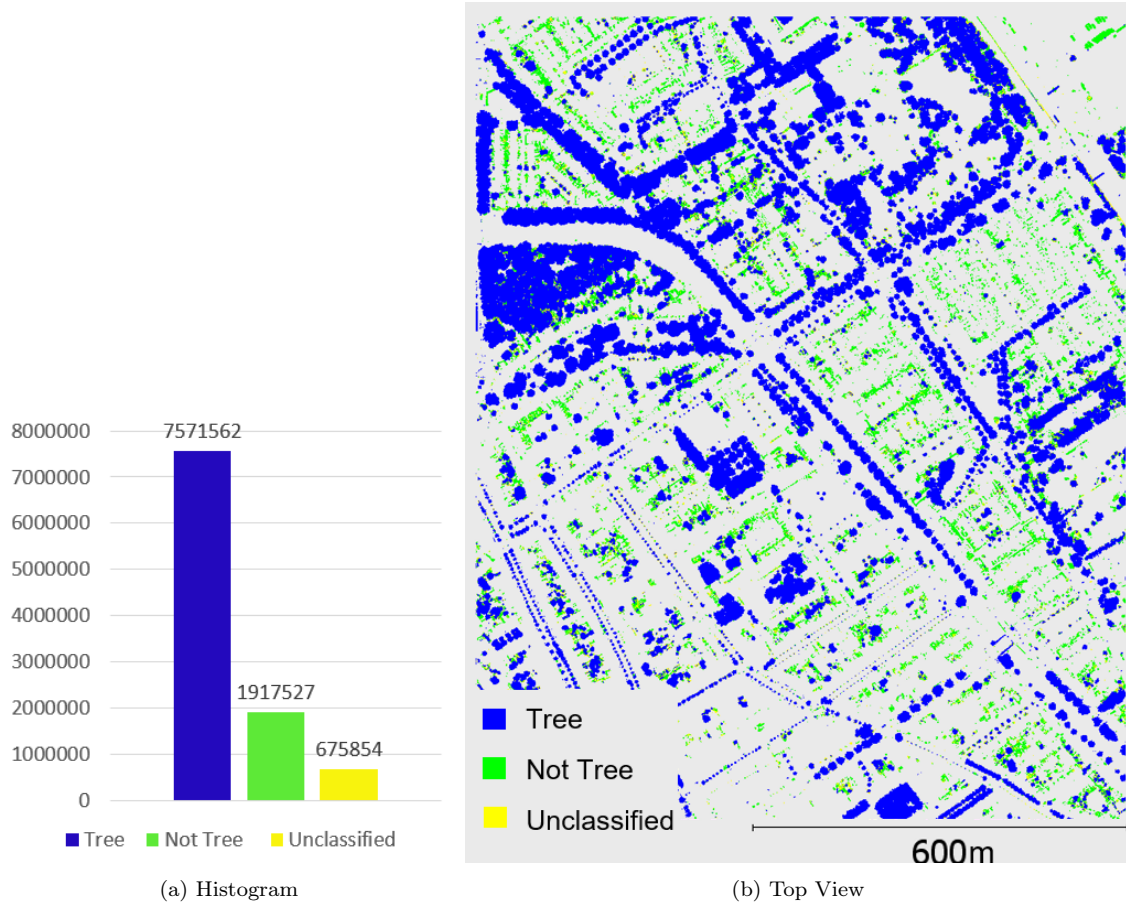


Figure 6.2: Histogram and top view of RF classified points, Tile 37EN1_10. A more detailed visualization of the RF results can be found in the appendix, see Figure A5.

Then the testing data is used to evaluate the accuracy of the model. In this case the accuracy was 92.66%. When applying the same model trained with the same training data on a different tile the accuracy is 88.43%. There is a limit to the testing data too. It is created manually and mainly well structured and clearly identifiable trees are used. This means the accuracy should be carefully interpreted, because it may not be representative of the actual accuracy on new, previously unseen and uncurated datasets. Furthermore, the accuracy is computed from manually selected points, therefore the computed accuracy relies on the accuracy of selecting tree and non tree points correctly manually. This means the performance accuracy tests only if false negatives are occurring within the testing data. This means false positives are not tested. As seen in the RF classification some false positives are occurring. This is mainly the case with tall vertical structures such as cranes on building sights, Figure 6.3.

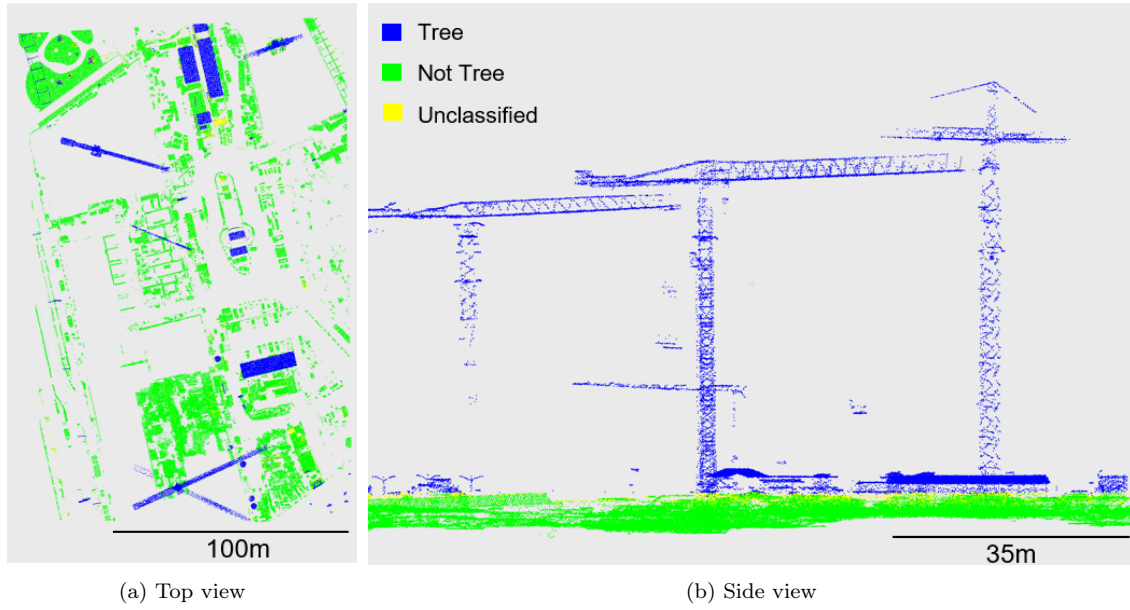
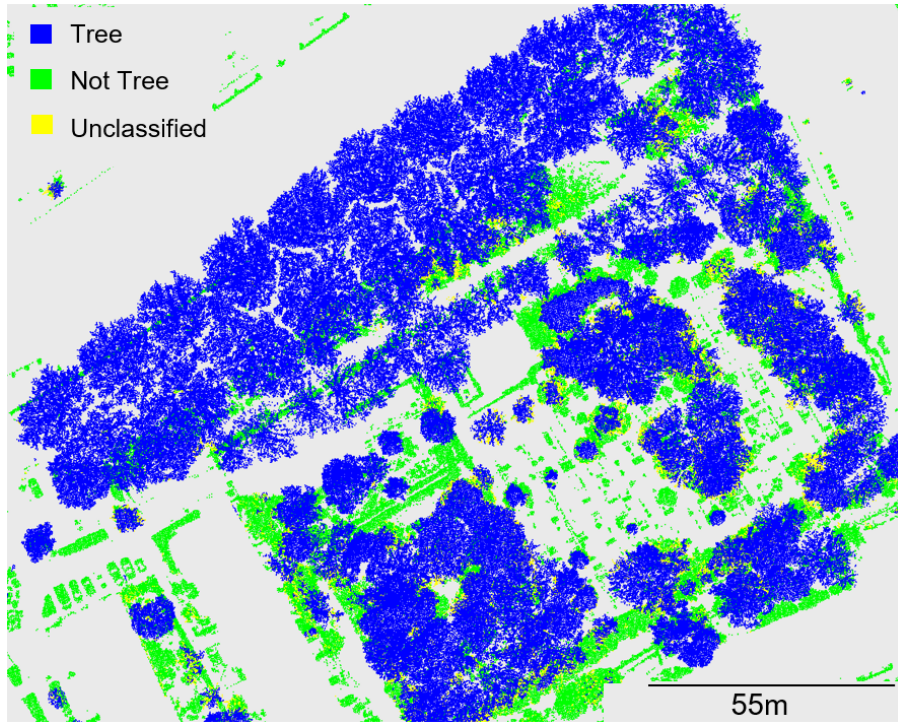


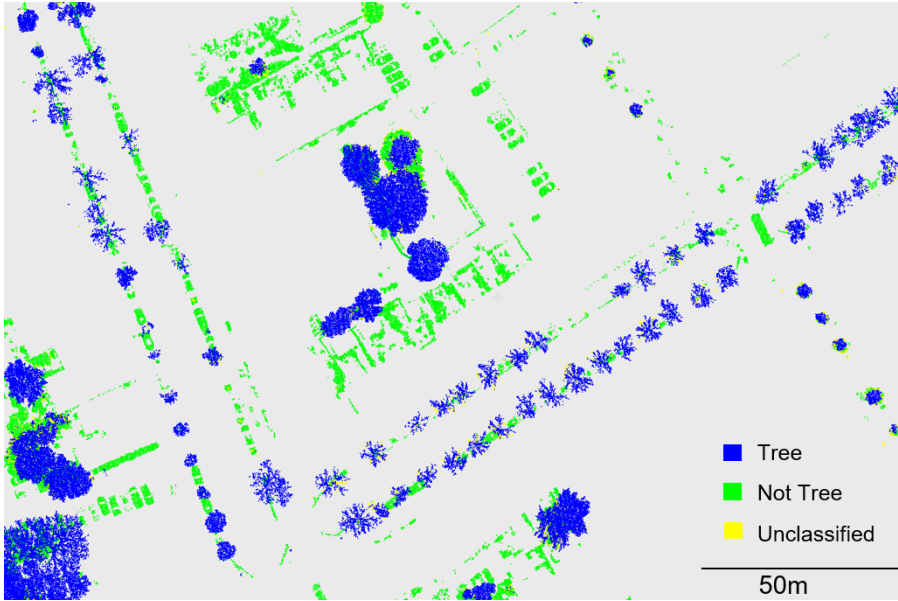
Figure 6.3: RF classification of the construction site near Delft station, where the cranes are classified as trees. Left: Top view, Right: Side view

To further improve the classification a distance computation is performed. The distance between all tree points classified by the RF model are used as a reference points and the distance too the entire unclassified points is computed. This is done since most points are miss classified near the edges of the tree. Some structures are miss classified but will remain. Some tree points are also not classified at all as trees.

Overall the RF classification performs rather well when classifying trees of different shapes and sizes, Figure 6.4. While some trees are missing some points due to the height filtering but also due to some misclassifications the result is satisfactory to move on to the next step.



(a) Dense, old and free growing trees



(b) Distant, young and managed trees

Figure 6.4: RF classification visual performance inspection showing promising classification results in different tree scenarios

6.2 Tree Segmentation Using Geometric Features

Tree points can also be segmented from the AHN4 data using geometric features to reduce the data. The PCA2, Roughness, sphericity and normal change of rate features were computed in

CloudCompare.

Based on visual inspection, the sphericity and PCA2 features determined using a voxel size 1.5m is used for this tile to filter out non tree points. In Figure 6.5 it can be seen that small structures such as street furniture like tram poles can be filtered out by removing points with a low PCA2 value. The threshold for this is chosen manually and was in this case 0.07. To remove flat surfaces such as initially misclassified parking lots or cars etc., the sphericity values are used. As indicated in Figure 6.6 low sphericity values indicate non tree values. By filtering these out, the dataset is almost completely reduced to only tree points.

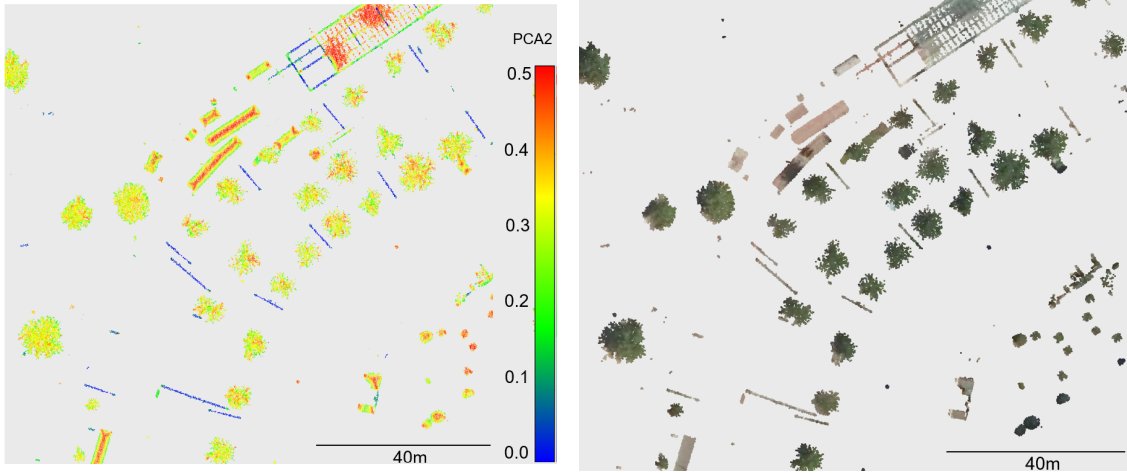


Figure 6.5: PCA2 geometric feature calculation on voxel sizes 1.5m

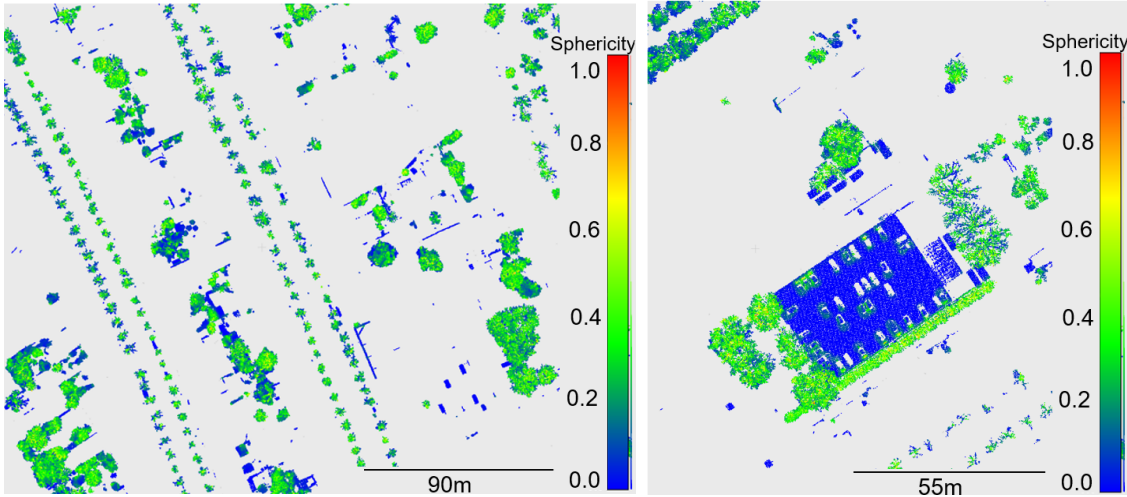


Figure 6.6: Sphericity geometric feature calculation on voxel sizes 1.5m in two different locations

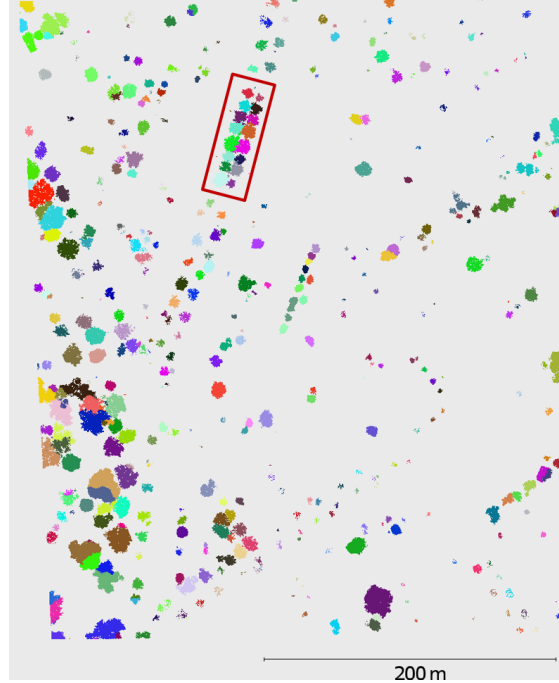
However, also this method has some drawbacks. The filtering often includes some tree points. This means the trees, while still identifiable, are reduced in point density. This is due to the variability in tree shape, size and point density. This means the uniform voxel size is not ideal for all these cases. The settings used result in an accuracy of only 65.73% for tile 37EN1_15 and 54.78% for tile 37EN1_10. While this method is faster and does not require the time consuming step of creating training data, it is not sufficient for further processing.

6.3 Individual Tree Segmentation

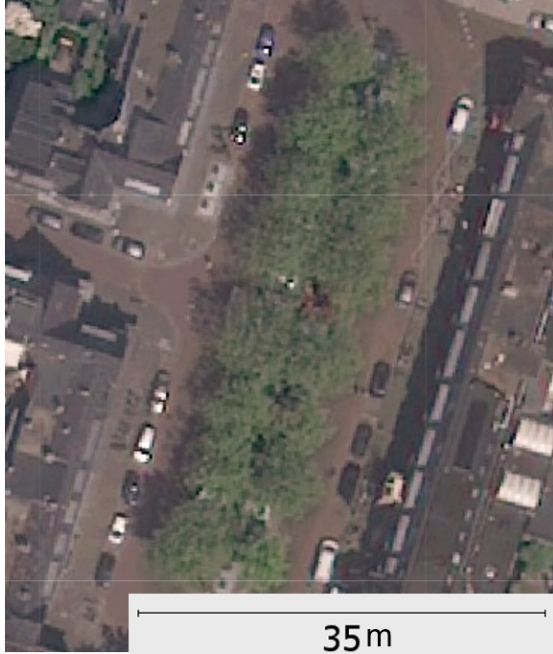
Using Individual Tree Detection (ITD) model individual trees are located and points are labeled with a tree ID, Figure 6.7, (J. Wang, 2018).



(a) RGB satellite image of larger area in Delft



(b) ITD result of larger area in Delft



(c) RGB satellite image of zoomed in area in Delft



(d) ITD result of zoomed in area in Delft

Figure 6.7: Individual Tree Detection result

6.4 Validation of Individual Tree Locations

To check the accuracy of the individual tree detection, the Delft Municipality Tree Inventory is used to cross reference if the trees are also found using the AHN4 data. This is based on the assumption that the Delft Municipality Tree Inventory is up to date meaning it is accurate and almost no trees are misplaced. During fieldwork it was established that while locations are mostly accurate the center location of the tree is not always accurate and the tree height and diameter are also rather inaccurate.

To evaluate the ITD the true positive accuracy using the Delft Municipality Tree Inventory is computed. For this trees which were correctly located within a 2.5m radius of the Delft Municipality Tree Inventory location are assumed to be correctly located.

6.4.1 Challenges and Limitations in Tree Detection

There are three main challenges and limitations regarding the individual tree detection which will be discussed, using examples in different areas in Delft, Figure 6.8, as specified below:

1. Trees are not detected at all
 - (a) Delft Station [1.1]
 - (b) Verwersdijk [1.2]
 - (c) Oude Delft [1.3]
2. A single tree is identified as multiple trees
 - (a) Paardenmarkt [2.1]
 - (b) Oude Kerk Delft [2.2]
3. Multiple trees are identified as a single tree
 - (a) Visbanken [3.1]
 - (b) Sint Agatha plein [3.2]
4. Falsely detected trees
 - (a) Verwersdijk 1 [4.1]
 - (b) Hippolytusbuurt 31 [4.2]
 - (c) Oude Delft 159 [4.3]

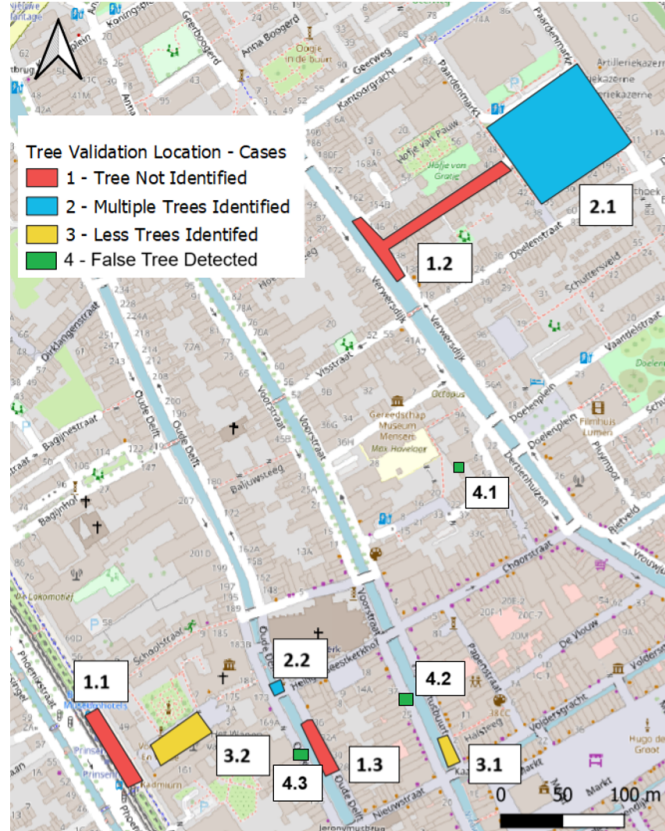


Figure 6.8: Location of cases discussing challenges and limitations of Tree Detection, where the numbering represents the case number.

Missed Detection

In case 1.1 (Figure 6.9) neither the Delft municipality dataset nor the ITD detects the trees. These trees are recently planted and are still rather young. With the removal of points below 2m, most

of the tree points are removed and the remaining points are most likely filtered out due to it being a small cluster of trees, Figure 6.10. The RF training data is also not constructed on many young trees since it is very hard to manually select many of those points.



Figure 6.9: Colored images of undetected trees in case 1.1 near Delft Station

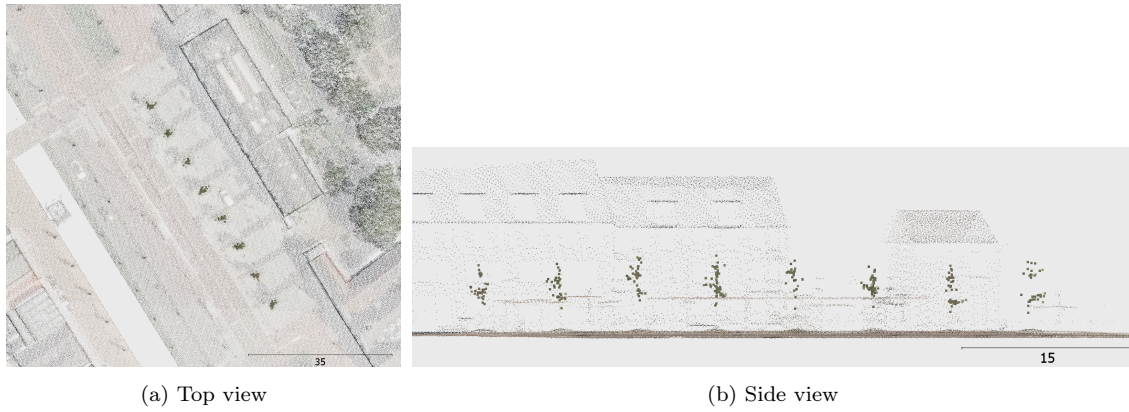


Figure 6.10: Undetected Trees for case 1.1 near Delft Station in RGB from AHN4, tree points are visualized in CloudCompare with point size 5 and the background point size is set to 1

In case 1.2 some trees are detected in row of trees along the canal. However, there are quite some trees missing, see Figure 6.11. In the figure it can also be seen that some private trees are detected with the ITD. The missing trees are newly planted and when comparing the Delft municipality dataset it becomes clear that the dataset is not up to date as the tree heights documented differ by more then 2m. In Figure 6.12 it can be seen that the point density of the missing trees is very low which causes them to be missing.



Figure 6.11: Colored images of undetected trees for case 1.2 at the Verwersdijk



Figure 6.12: Undetected Trees in case 1.2 near Verwersdijk in RGB from AHN4, tree points are visualized in CloudCompare with point size 5 and the background point size is set to 1

In case 1.3 one tree is not detected in a row of trees, Figure 6.13. This tree is much smaller and younger, Figure 6.14. While the tree is documented in the Delft Municipality Tree Inventory the RF and ITD filter the tree points out.

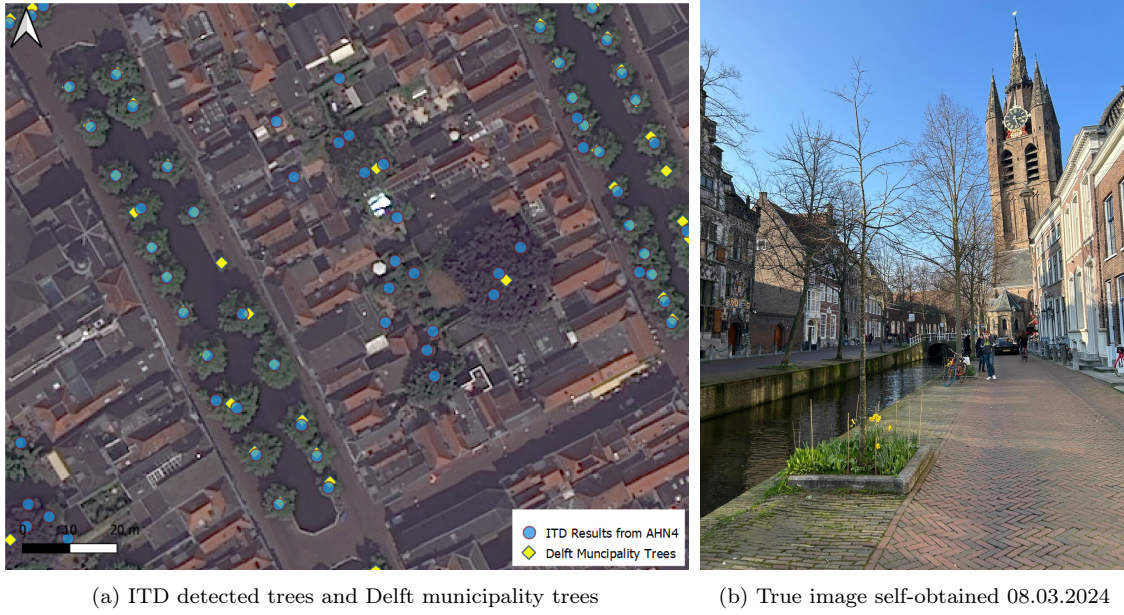


Figure 6.13: Colored images of undetected trees in case 1.3 near Oude Delft

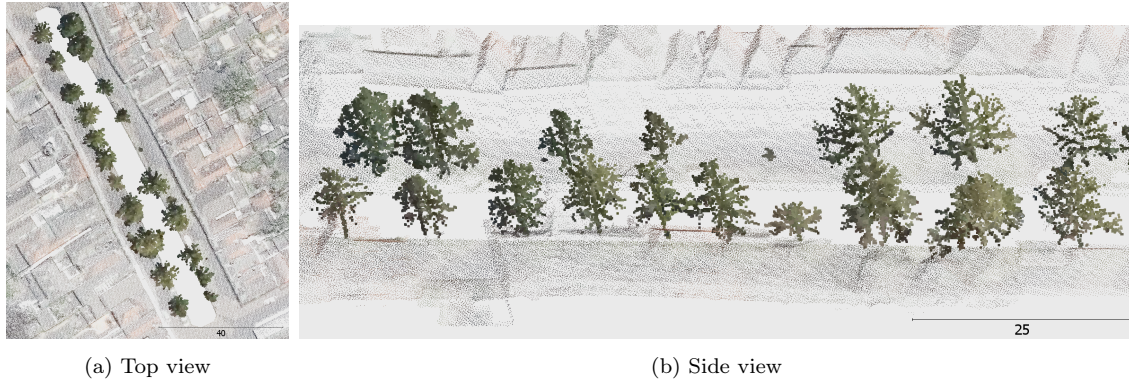


Figure 6.14: Undetected Trees in case 1.3 near Oude Delft in RGB from AHN4, tree points are visualized in CloudCompare with point size 5 and the background point size is set to 1

The most noticeable missing trees are small trees with low density branches, which often are young trees. The main factor for trees being not detected from AHN4 is due to them not being classified as trees in the RF classification after most of the tree points are removed when removing points below 2m. This is due to the limited training data on small and young trees. If some tree points were classified as trees, the ITD has a filter set where clusters with small point counts are removed. This is to filter out small bushes or street furniture that is not removed before.

To limit this issue the RF training data will need to be improved. If smaller trees can be detected and more street furniture is filtered out, the ITD can be run on all points which will result in more small trees being detected.

Single Tree identified as Multiple Trees

Some cases show that multiple trees are not separated with the ITD and are classified as a single tree. Two locations are being discussed where this occurred. In the first case multiple trees are

not separated correctly near the Paardenmarkt [case 2.1]. A second location where this occurred is near the Oude Kerk in Delft [case 2.2].

The first case, 2.1, shows that very large and old trees at the Paardenmarkt are not correctly identified. The trees at Paardenmarkt are planted relatively close so that some tree crowns are overlapping. Furthermore, the trees are splitting off, Figure 6.15. There are some trees that are correctly identified. However it can be seen that in some cases where there is supposed to be one tree, the ITD identifies multiple. When comparing these tree locations with the height map, Figure 6.16, It can be noticed that the issue is caused due by the tree crown having multiple local maxima that are misinterpreted as a new tree crown peak in the ITD. These multiple peaks occur due to the multiple splits in big branches in the tree. The crowns are also very large, therefore the setting of the search radius in the ITD might be too small.

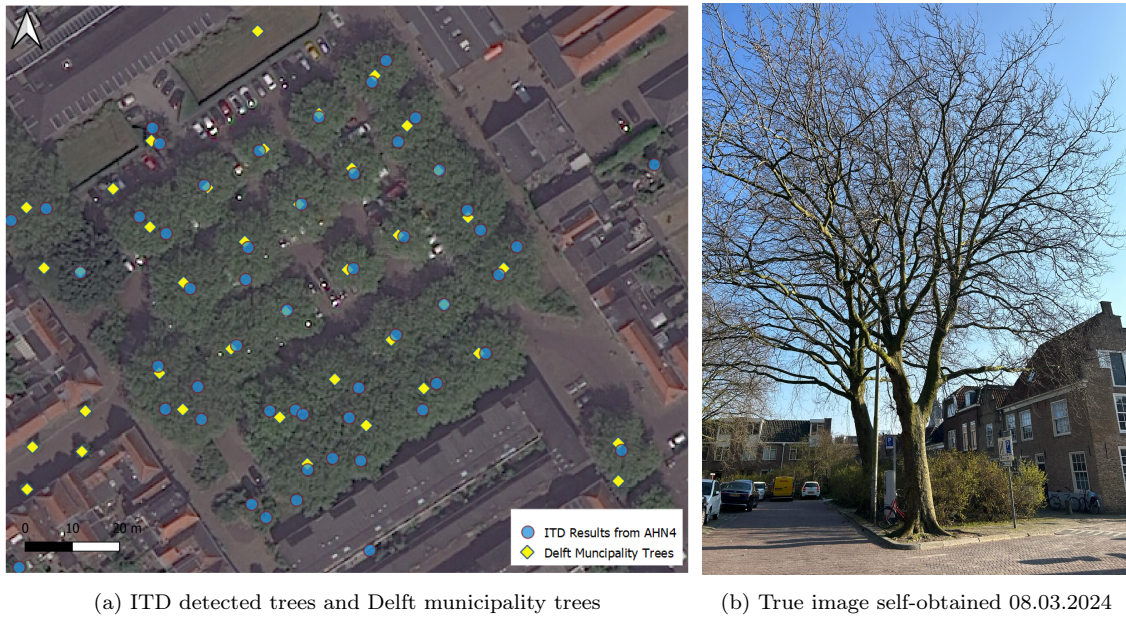


Figure 6.15: Colored images of trees in case 2.1 at Paardenmarkt in Delft

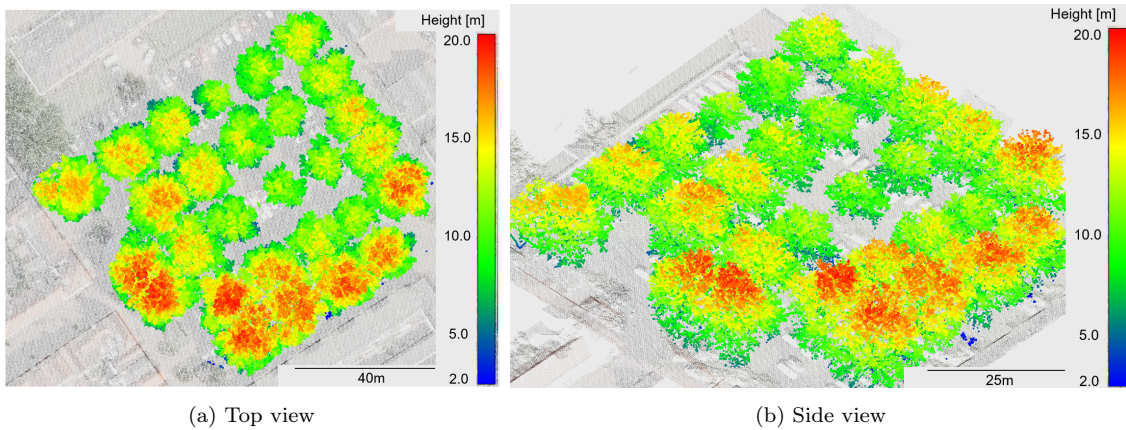
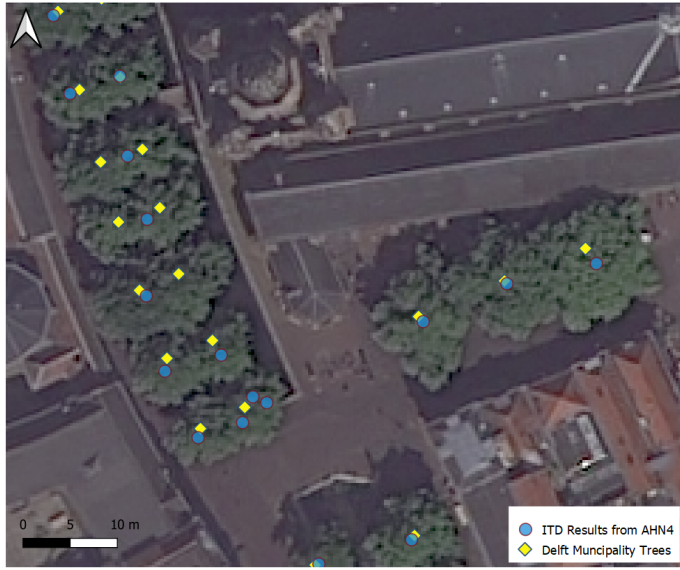


Figure 6.16: Trees in case 2.1 at Paardenmarkt in Delft from AHN4, tree points are visualized in CloudCompare with point size 5 and the background point size is set to 1

In case study 2.2, the tree under observation exhibits significant branching and is subject to various external influences that result in an irregular growth pattern in its crown. Its growth is constrained in one direction by the proximity of other trees, although there is plenty of space for growth above the water on the other side, as shown in Figure 6.17. This leads to an imbalance in the tree crown, complicating the interpretation of the ITD. Furthermore, the crown's division into multiple branches could be misinterpreted as indicating several distinct trees. The branching also results in a three distinct maximum height points which correlate with the individual tree location detected with the ITD, Figure 6.18. The presence of a nearby street lamp means tree management is required to prevent interference with the lamp, which also alters the natural growth pattern of the tree.



(a) ITD detected trees and Delft municipality trees



(b) True image self-obtained 08.03.2024

Figure 6.17: Colored images of trees in case 2.2 near the Oude Kerk in Delft

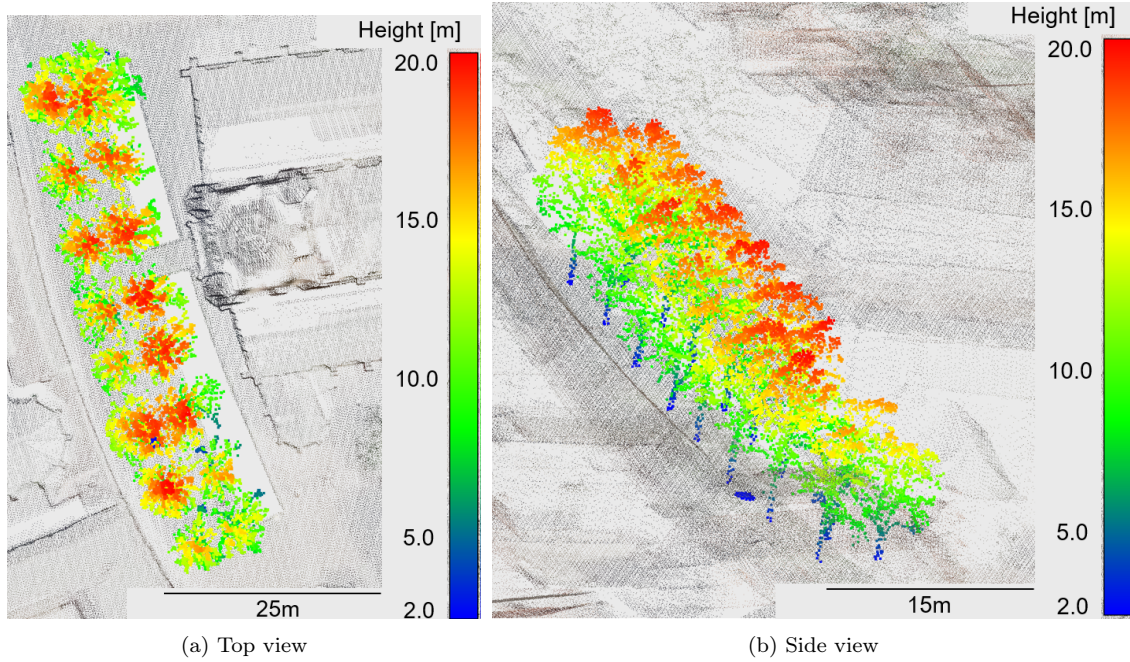


Figure 6.18: Trees in case 2.2 near the Oude Kerk in Delft from AHN4, tree points are visualized in CloudCompare with point size 5 and the background point size is set to 1

Overall, the causes that result in multiple trees identification rather than one tree with the ITD stem from a combination of natural growth patterns and external environmental pressure. In case 2.1, the close proximity and overlapping crowns of large trees at Paardenmarkt, coupled with multiple crown splits, lead to the misidentification of tree crowns in the ITD process. This is further complicated by the inadequate settings of the ITD's search radius for the large tree crowns. On the other hand, case 2.2 highlights how spatial constraints and human interventions, such as tree management near infrastructures like street lamps, result in irregular and unbalanced tree growth. This causes the ITD to misinterpret single trees as multiple entities due to the appearance of distinct crown peaks.

Multiple Trees Identified as Single Tree

While some trees are split into multiple trees, the opposite can also occur. In that case multiple trees are identified as a single tree. Two cases where multiple trees are not separated correctly are discussed, case 3.1 near Visenbanken and case 3.2 on the Sint Agatha plein.

In the first case, 3.1, the trees are planted rather close together. They have a very dense network of branches that intertwine, Figure 6.19. While there are five trees, the ITD only locates two. Multiple peaks can be seen in the side profile, Figure 6.20, the distance between these peaks is too small so the ITD merges them and only detects two main tree peaks.



Figure 6.19: Colored images of trees in case 3.1 near the Visbanken in Delft

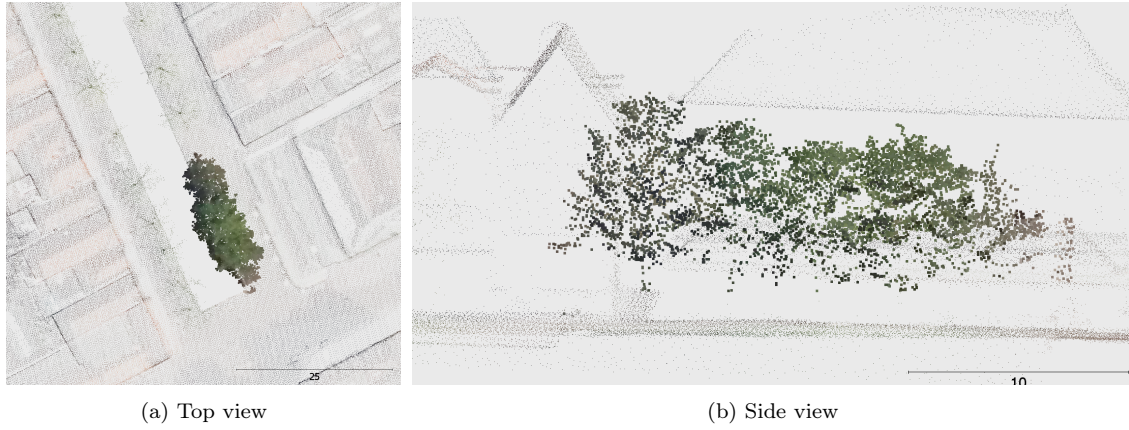


Figure 6.20: Trees in case 3.1 near the Visbanken in Delft from AHN4, tree points are visualized in CloudCompare with point size 5 and the background point size is set to 1

In the second case the trees are planted far apart but still have intertwining branches. However, the main cause of the ITD identifying three trees as one, is due to the human interference in the tree growth. As seen in Figure 6.21 the tree trunk tops are cut. This causes the tree to not have its original tree peak. The tree crowns then merge into one large crown that is misinterpreted as one tree, Figure 6.22.

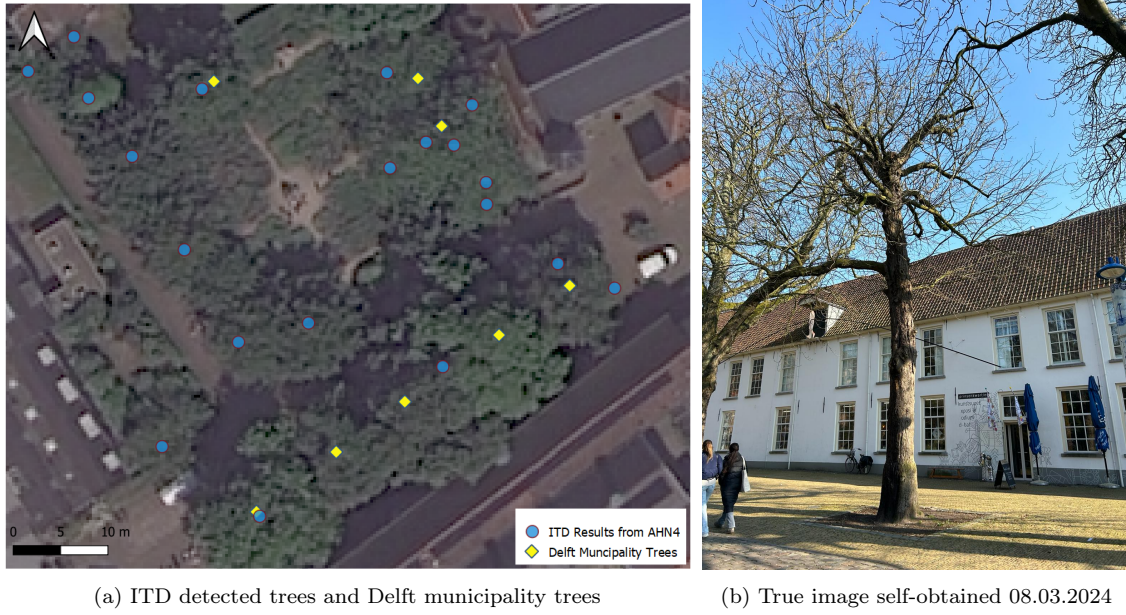


Figure 6.21: Colored images of trees in case 3.2 near the Sint Agatha plein in Delft

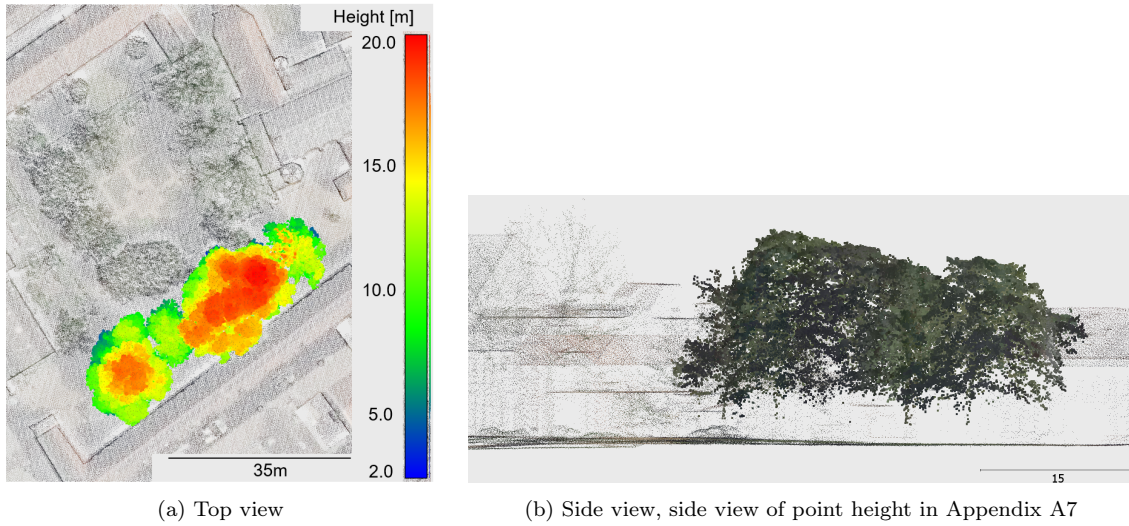


Figure 6.22: Trees in case 3.2 near the Sint Agatha plein in Delft from AHN4, tree points are visualized in CloudCompare with point size 5 and the background point size is set to 1

The tree density and branches interference greatly influences the accuracy of the ITD. If the trees are planted very close and have very a dense intertwining crown then the search radius is too large to distinguish between two individual trees. Furthermore, the intervention of humans cause irregularities in the tree crown which can cause the trees to to have its original crown peak therefore leading to errors in the ITD.

False Tree Detection

In some cases trees are detected that are not recorded in the Delft Municipality Tree Inventory. In the selected study area 460 extra trees are detected. However, some of the detected trees are

not true trees. Three cases are evaluated where either buildings, street furniture or tree structures cause faulty tree detection.

In the first case, case 4.1 seen in Figure 6.23, the identified tree is falsely detected because in the pre-processing of the AHN4 data the building points were not correctly classified. The gutter of the building was not classified as part of the building. The Random Forest classification was then also not able to filter this out either. This error propagated and results in a faulty tree detection with the ITD.

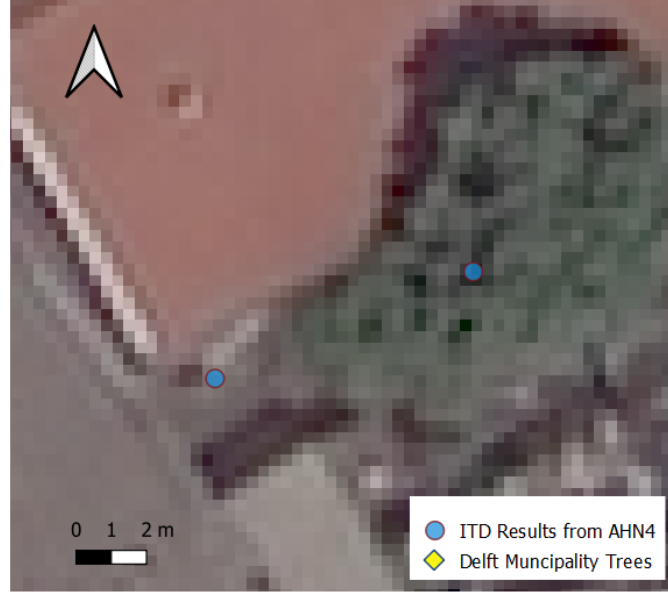


Figure 6.23: True image self-obtained 12.05.2024 of falsely detected trees in case 4.1 near Verwersdijk 1 in Delft

The street furniture is part of the AHN4 class that is processed in this study. This often intertwines with the vegetation such as trees. Separating them can be done to some extent using the RF classification but as mentioned the RF is limited when the trees and street furniture is very close to each other. This is the case for 4.2, Figure 6.24. In this case there is a street light hanging on a cable between the tree and the houses. The reflective characteristics of the lamp and the cable is very different to the tree but due to the overlap of branches and lamp and cable the RF is incapable to distinguish between them. The ITD is able to identify that there is a difference and separates the lamp.



(a) ITD detected trees and Delft municipality trees

(b) True image self-obtained 12.05.2024

Figure 6.24: Images of falsely detected trees in case 4.2 near Hippolytusbuurt 31 in Delft

The last case, 4.3 shown in Figure 6.25, a combination of case 4.2 and cases 3. Here a single tree has a very spread structure and street furniture is present resulting in faulty tree detection.



(a) ITD detected trees and Delft municipality trees

(b) True image self-obtained 12.05.2024

Figure 6.25: Images of falsely detected trees in case 4.3 near Oude Delft 159 in Delft

6.4.2 Successes of ITD

While the ITD has some limitations, still 69.58%, 458 trees, of the municipality trees are correctly identified within a 2.5m radius using the ITD, Table 6.1. The ITD also finds 460 additional trees

in the study area. The missing trees are mainly small trees that are either not detected by the RF or have too little points for the ITD.

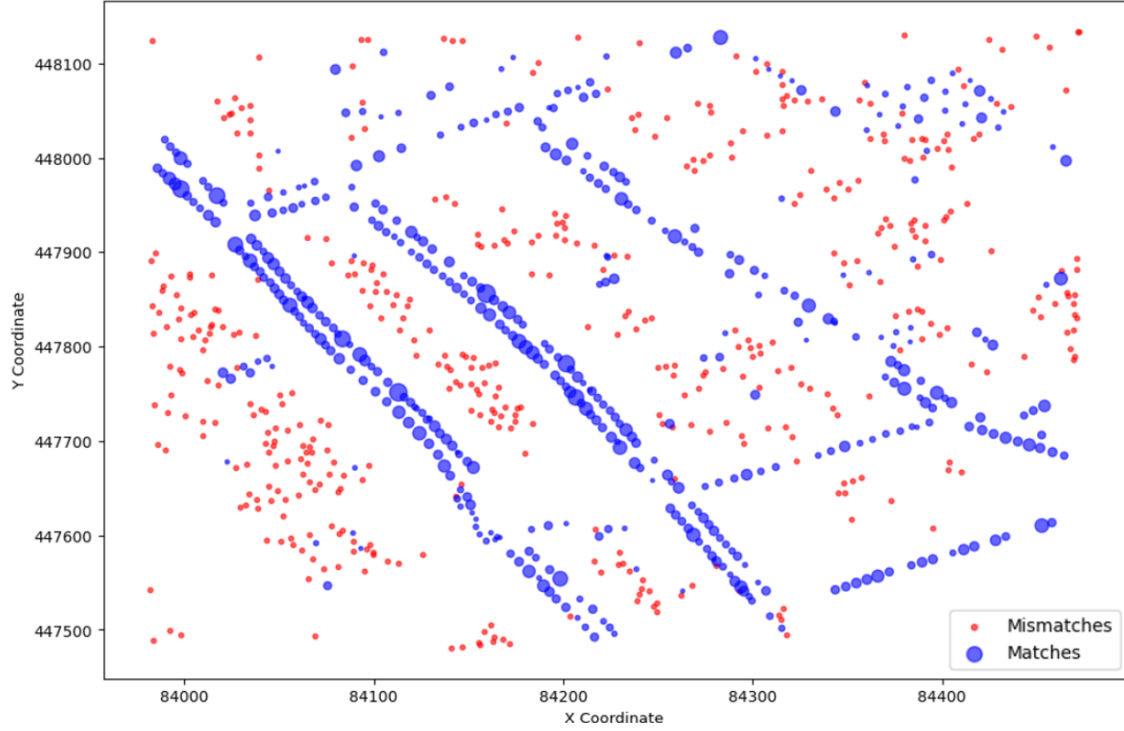


Figure 6.26: Validation points between ITD results and Delft Municipality Tree Inventory

Statistic	Value
Count	458
Mean	0.711
Standard Deviation	0.546
Minimum	0.012
25th Percentile	0.335
Median (50th Percentile)	0.540
75th Percentile	0.889
Maximum	2.459

Table 6.1: Statistical summary of ITD validation data within 2.5m

To evaluate the accuracy of the ITD trees, a radius of 2.5m is chosen. This distance between the ITD and Delft Municipality Tree Inventory is based on the accuracy plateaus. The accuracy of detecting the correct location can be evaluated when looking at the histogram of the distances between the two tree locations, Figure 6.26. The mean distance of all points within 2.5m radius is 0.71m. This shows that most tree locations, if detected correctly, are detected within a 1m horizontal distance.



Figure 6.27: ITD validation using Delft Municipality Tree Inventory

The ITD identified 460 additional trees shown, in green in Figure 6.27. When looking closer, the accuracy is around 70% when predicting the tree locations of the Delft municipality trees. There are some issues to be aware of. In some locations the Delft municipality tree inventory dataset shows tree locations although there are no trees, Figure 6.28a. The ITD correctly predicts that there are no trees at these locations. These trees may have been removed recently. This means recent changes of municipality trees can be detected using ITD and RF. However, this needs to be validated physically to rule out small/young trees that are not detected in the LiDAR and the spectral images.



(a) Trees registered in Delft tree inventory dataset but not Identified in ITD

(b) Tree locations better and more accurately detected using ITD compared to Delft municipality tree inventory.



(c) Non-municipality trees detected using ITD

Figure 6.28: Improvements in detecting tree locations in Delft using ITD

In some park areas, some trees are registered in the Delft Municipality Tree Inventory. However, the locations seem to not be very accurate. Using the ITD more trees and more accurate locations of trees can be identified, Figure 6.28b. The ITD also finds additional trees that are not part of the municipality tree. For example trees located in private gardens, Figure 6.28c. These trees are significant when finding the true tree count in the city as well as when evaluating the biodiversity and biomass. There are a significant amount of additional trees that are detected and they can have a significant impact on environment. By detecting them their influence can be evaluated further.

6.5 Tree Feature Extraction

After detecting the tree locations, the tree features are extracted. The LiDAR and spectral images are used to extract the tree features described in Table 5.4.

6.5.1 LiDAR Tree Features

Geometric features are computed using the airborne LiDAR data with a Python algorithm to find the tree heights, crown diameter and the sphericity, Figure 6.31. These values are very hard to validate. On the other hand some objects wrongly classified as trees should have rather odd geometric features and are filtered out. Similarly, some trees are merged during the Individual Tree Segmentation and show a rather large tree diameter.

6.5.1.1 Tree Height The maximum height for each individual tree is computed, Figure 6.29. Where the ITD and the Delft Municipality Tree Inventory have a match within 2.5m and the dataset has a height registered, then the heights are compared, Figure 6.30. There are 28 trees without a height description. The mean difference in height is 2.6m which is relatively small when comparing tree heights, Table 6.2. It is unknown when the tree heights were written measured. The heights are an estimate in the Delft municipality dataset and are mostly an estimate with 1.5m uncertainty. This means the dataset is rather accurate. However, there are some larger differences, up to 14m, where the height computed and registered are very off.



Figure 6.29: Maximum tree heights of ITD detected trees



Figure 6.30: Height Difference of matching trees of the Delft municipality trees and ITD

6.5.1.2 Tree Crown Sphericity The sphericity is computed for each tree by evaluating how well the points fit within a sphere, Figure 6.31. The results are a sphericity value between 0 and 1.

Statistic	Value
Count	430
Mean	2.615
Standard Deviation	1.749
Minimum	0.0150
25th Percentile	1.185
Median (50th Percentile)	2.653
75th Percentile	3.799
Maximum	14.734

Table 6.2: Statistical summary of tree height difference data

Where 1 indicates a perfectly spherical shape. The lower the value, the less the data fit a sphere.

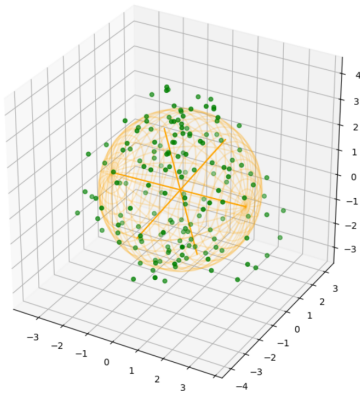


Figure 6.31: Example of point cloud of the sphericity of a tree

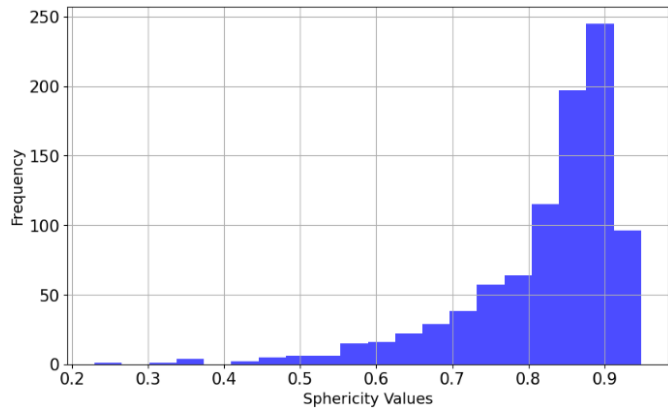


Figure 6.32: Histogram of sphericity values

The mean sphericity is 0.821 and shows that in general all trees are rather spherical, Table 6.3. The histogram, Figure 6.32, also shows that the majority of trees are close to spherical. When comparing the height map, Figure 6.29 and 6.33, it can be seen that smaller trees tend to have a lower sphericity value. This can be caused by multiple reasons. Small trees have less points and therefore it is harder to fit a sphere. Secondly small trees can be cut off when the lower 2.5m was removed. Furthermore, some tree species grow a rather oval-shaped crown ([Washington State Department of Natural Resources, 2016](#)). Another reason of trees having a non-spherical crown can be that trees are pruned. Topiary trees, trees cut into specific shapes, are one example where the tree crown shape is altered which in some cases is to non-spherical shapes. Often topiary trees are quite small to be maintained easier.

Statistic	Value
Count	919
Mean	0.821
Standard Deviation	0.103
Minimum	0.229
25% Percentile	0.785
Median (50% Percentile)	0.856
75% Percentile	0.894
Maximum	0.948

Table 6.3: Statistical summary of sphericity data

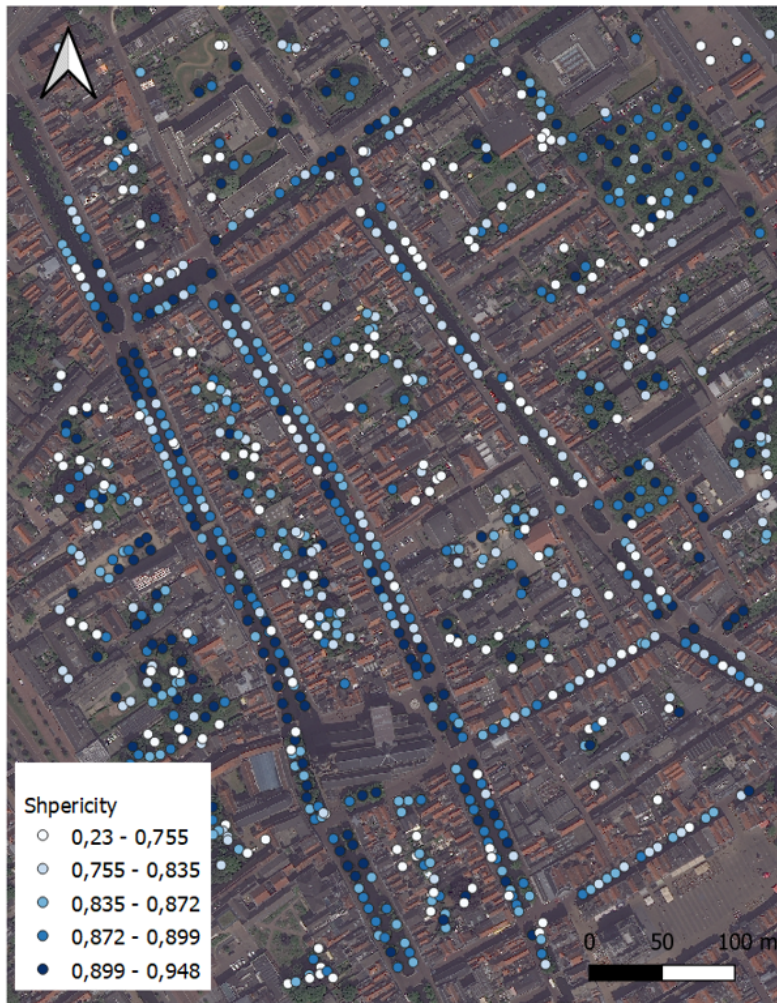


Figure 6.33: Sphericity values for ITD trees

6.5.1.3 LiDAR Tree Feature Correlation The correlation between some of the tree features extracted from the LiDAR data are computed, Figure 6.34, where -1 indicates a negative correlation, 0 no correlation and +1 a positive correlation between the features. Their correlation can be summarized as follows:

- Height (z): There is a very strong positive correlation between median height (z_{med}) and maximum height (z_{max}), indicating that trees with greater median heights typically also reach higher maximum heights. Both median and maximum heights moderately correlate with sphericity (sph), suggesting that taller trees may have a more spherical canopy.
- Intensity (i): Median intensity (i_{med}) does not exhibit a strong correlation with height or sphericity, which indicates that the strength of the LiDAR return does not consistently vary with these factors. However, median and maximum intensities (i_{med} and i_{max}) are moderately correlated, implying some consistency in the intensity readings within individual trees.
- Number of Returns (NoR): The median number of returns (NoR_{med}) shows a weak positive correlation with median height, while the maximum number of returns (NoR_{max}) has a moderate positive correlation with both median and maximum heights, which might reflect that taller trees or those with complex structures return more signals.
- Sphericity (sph): There is a moderate positive correlation between sphericity and median height (z_{med}), indicating that trees of medium height are more likely to exhibit a spherical shape. The relationship between sphericity and intensity is not pronounced, suggesting the shape of the tree canopy is not significantly influenced by the intensity of the reflected returns.

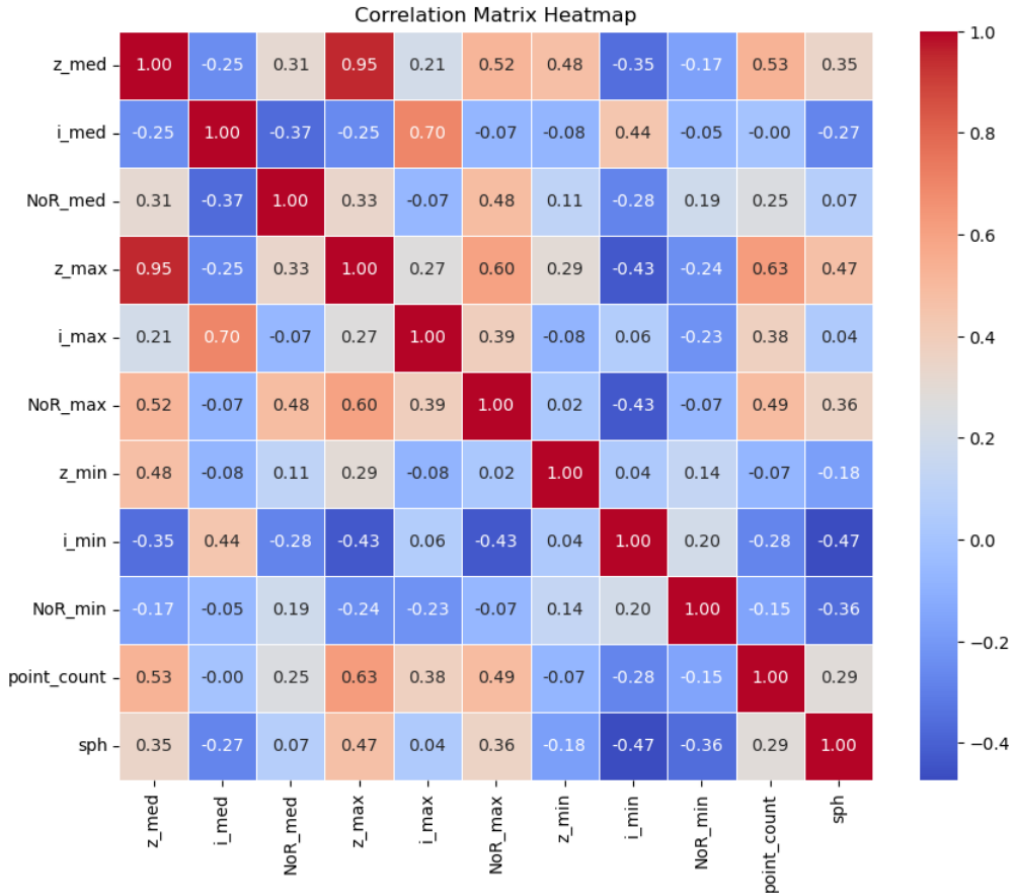


Figure 6.34: Confusion Matrix of LiDAR tree features

6.5.2 Spectral Data Tree Features

The feature extraction is performed after the points are labeled accounting to the Individual Tree ID. Then the mean 2D location is found to determine the tree center location. These locations are then used in the re-projected mosaics to find the center pixels of the tree. This gives the tree RGB and NIR data, Figure 6.35 and Figure 6.36.

6.5.2.1 RGB In the RGB images of the different times (Figure 6.35) it can be seen that in spring, on 04-05, small trees show little to no leaves yet. In late spring, the trees have significant foliage. In August the tree RGB values are higher and the leaves are becoming darker compared to in spring. In Fall on 17-10 the leaves are much darker and are becoming less dense again.



Figure 6.35: Four images showing the RGB variation between late spring, summer and beginning of fall in 2023.

Statistic	Red	Green	Blue
Mean	81.072	84.533	78.645
Standard Deviation	15.023	16.053	13.053
Minimum	44.06	25.50	46.50
25%	75.187	78.375	74.312
75%	87.625	93.937	84.125
Maximum	149.062	141.750	140.312

Table 6.4: Statistics of Red, Green, and Blue channels for spring image, 04-05-2023

6.5.2.2 Near Infrared (NIR) The NIR is extracted from the mosaics from each seasonal image. The NIR is used to detect the trees health through computing the NDVI.



Figure 6.36: Four images showing the NDVI variation between late spring, summer and beginning of fall in 2023.

6.5.2.3 Seasonality and Temporal changes The seasonal variability can be evaluated when comparing the RGB and NDVI values for the four different time periods. The provided histograms,

Figure 6.37, represent the RGB (Red, Green, Blue) pixel intensity distributions across different seasons. Each histogram highlights how the colors in a landscape change throughout the year, a key factor in vegetation monitoring and environmental studies. The summary of each season's color profile is as follows:

1. **Spring, Figure 6.37a:**

- The **Green channel** is highlighting the growth of fresh leaves and grass.
- The **Red channel** follows, less intense than green, suggesting the presence of budding plants and some flowers.
- The **Blue channel** has a high intensity indicating that some trees are not yet showing leaves so all bands are present representing either the tree bark color or ground.

2. **Late Spring , Figure 6.37b:**

- The **Red and Green channels** are similar, peaking around mid-intensity, with red showing a slightly wider distribution indicating the presence of healthy foliage.
- The **Blue channel** is also well-represented, indicating a balanced color reflection typical of late spring.

3. **Summer, Figure 6.37c:**

- The **Green channel** remains dominant, indicating lush, mature vegetation.
- The **Red channel** is less intense than green but more than blue, reflecting a mix of healthy vegetation and areas with dry or stressed foliage.
- The **Blue channel** shows the least intensity, consistent with typical vegetation reflectance under strong summer sunlight.

4. **Fall, Figure 6.37d:**

- The **Red channel** shows a wider spread with a peak at mid-intensity, indicative for the beginning of autumn's rich red foliage.
- The **Green channel** has lower intensity, suggesting diminishing greenery.
- The **Blue channel** has a high peak mid intensity with a small spread, reflecting blue light reflection by autumn colors.

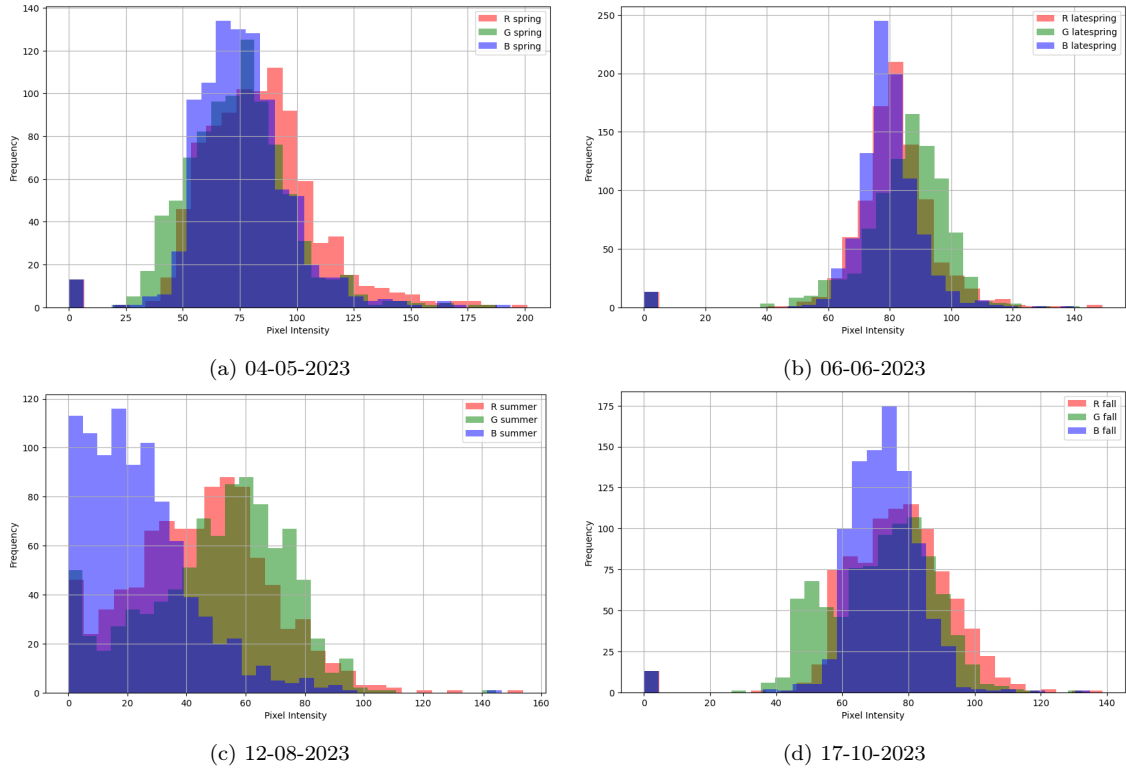


Figure 6.37: Four images showing the RGB histogram variation between late spring, summer and beginning of fall in 2023.

To evaluate the seasonal differences, the NDVI is also quite indicative of the trees seasonal growth. The statistics of the NDVI of all trees is shown in Table 6.5. In spring, the mean NDVI is relatively low around 0.25 which indicates that not all trees are showing leaves yet. Some trees have flowers which also will influence the NDVI negatively. The variance is larger in spring compared to late spring when most trees have now leaves. In spring, the mean NDVI is above 3 indicating a healthy vegetation index. Since the leaves are young and healthy due to the recent growth, the NDVI is highest in late spring. After spring, summer is relatively dry and sunny which was true for summer 2023 in Delft (Huiskamp, 2024), this effected the NDVI recorded in August. In summer, the NDVI decreases compared to spring. In fall, the mean NDVI is similar to the mean NDVI in summer, however the variance increases and the minimum recorded NDVI is much more extreme compared to summer. This can be contributed to the fact that in fall more rain provides some replenishment for some trees increasing their NDVI while other trees are starting to be effected by temperature changes and starting to get brown leaves or losing leaves. These trends correspond with the recorded climate where with an average temperature of 18.4 °C, the summer of 2023 ranked among the top 10 warmest since records began in 1901, exceeding the normal average of 17.4 °C (Huiskamp, 2024). Additionally, it was notably sunny, recording 752 hours of sunshine compared to the normal 619 hours (Huiskamp, 2024). The autumn followed with exceptionally mild temperatures, marking the second mildest since records began. October and November were particularly wet months, contributing to an average precipitation across the country of 365 mm, significantly higher than the normal 222 mm (Huiskamp, 2024).

Table 6.5: Seasonal NDVI Statistics

Statistic	NDVI_spring	NDVI_latespring	NDVI_summer	NDVI_fall
Count	919	919	919	919
Mean	0.256	0.414	0.324	0.324
Standard Deviation	0.178	0.129	0.106	0.156
Minimum	-0.287	-0.322	-0.037	-0.598
25%	0.107	0.360	0.273	0.229
50%	0.223	0.429	0.340	0.344
75%	0.400	0.499	0.393	0.443
Maximum	0.799	0.780	0.648	0.733
Variance	0.032	0.017	0.011	0.024

The distribution of the NDVI is visualized in a histogram, Figure 6.38. In the histogram it can be noticed that a small amount of trees have a very low or negative NDVI in all seasons, even in summer. This can be caused by three factors; 1) the location detected is not correctly identifying a tree, 2) the tree is of poor health, or 3) the tree is too small to substantially affect the NDVI value of a 0.9x0.9 grid cell. Overall, it can be seen that there is a significant overlap in the NDVI especially in late spring, summer and fall. This overlap is around a 0.4 NDVI indicating a general good vegetation health and density.

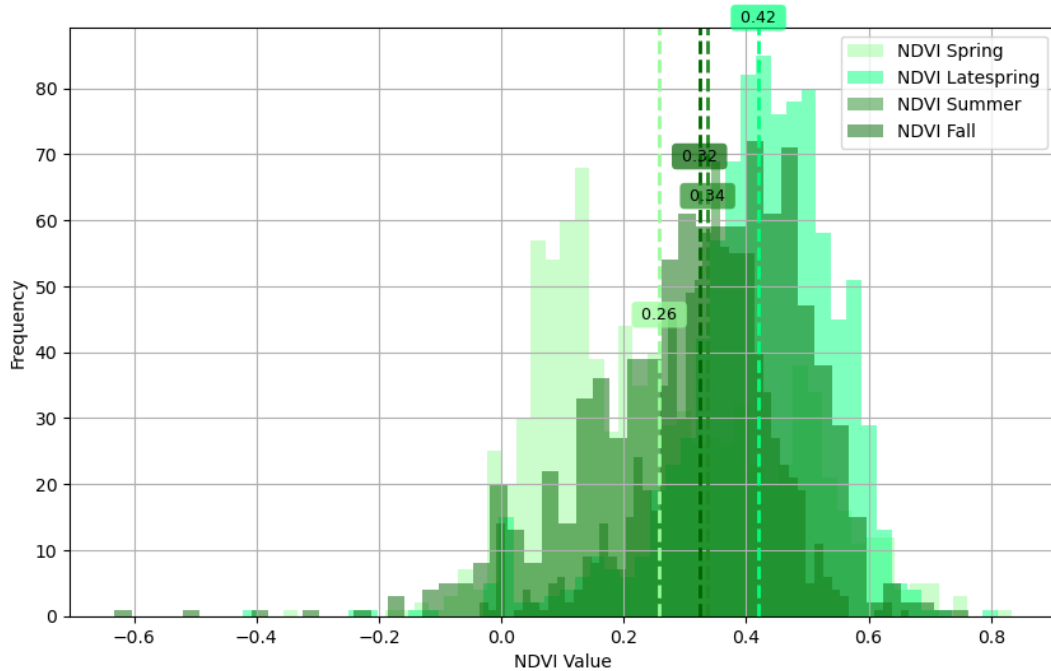


Figure 6.38: Histogram of NDVI for the four different time periods 5.3

6.6 Clustering

Using the tree features a K-Means clustering methods was implemented. To evaluate the impact of combining the MS and LAS data three different scenarios are analyzed. The first clustering is

computed using both the ALS and MS features, second only the ALS, third only the MS features were used in the algorithm. Additionally, two different number of cluster (k), $k=15$, $k=8$, and $k=30$, are analyzed. The clustering results are analyzed with using the tree species recorded in the Delft Municipality Tree Inventory, Figure 6.39.



Figure 6.39: Tree Species recorded in the Delft Municipality Tree Inventory

In the study area selected the Delft Municipality Tree Inventory recorded 61 different tree species. It can be seen that most streets are vegetated using the same tree species. However, as seen in Figure A2, the tree ages or time of plantation sometimes varies along the streets. Overall the clustering results are expected to show similar results.

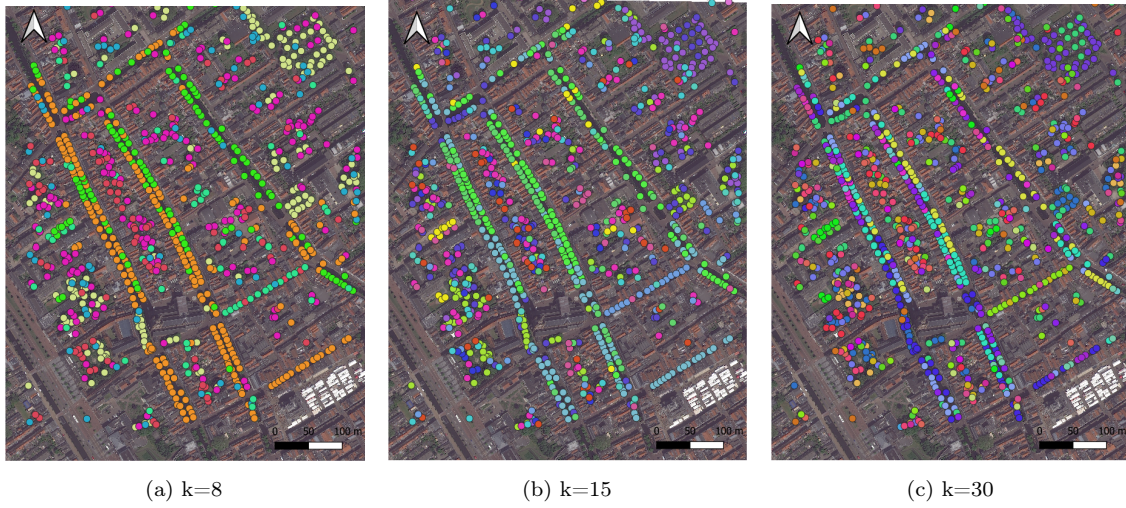


Figure 6.40: K-means clustering using both ALS and MS features for three scenarios: a) $k=8$, b) $k=15$, c) $k=30$.

As the Delft Municipality Tree Inventory recorded 61 different tree species at first a K-means clustering with a higher k is evaluated. In the case of a K-means clustering with $K=30$, Figure 6.40c, the number of clusters is too large and the trees are over-clustered. It can be noticed that where differences should be detected this can be done with $k=15$, Figure 6.40b. In this case similarities between trees are also still detected which is less present with a higher clustering number of $k=30$. With a very low clustering number of $k=8$, Figure 6.40a, more similarities can be detected but it can also cause under-clustering. Based on these results the clustering number $k=8$ and $k=15$ are further evaluated.

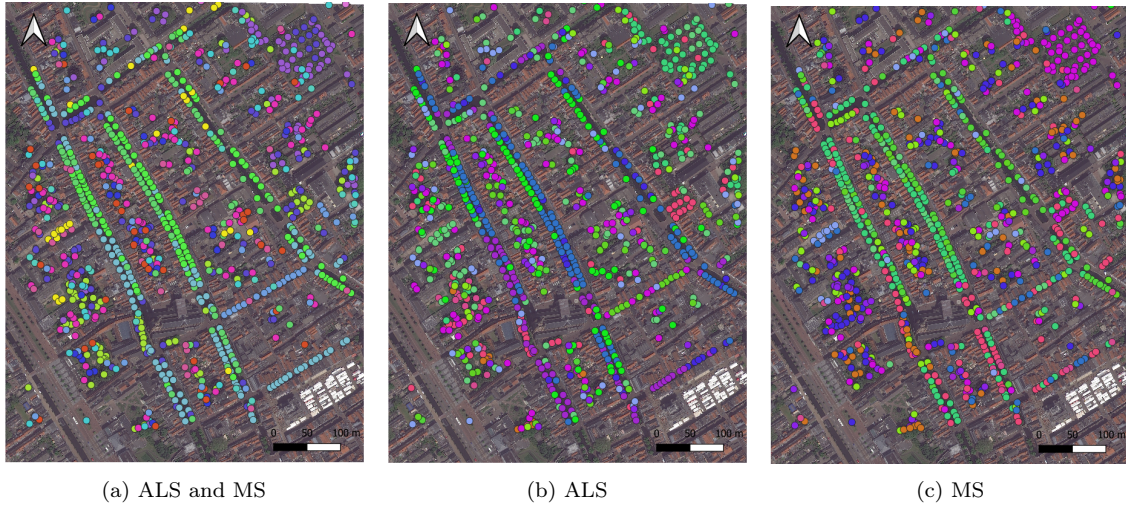


Figure 6.41: K-means clustering with $k=15$ for three scenarios: a) Combination of feature in put of ALS and MS, b) Only ALS features and tree location as input, c) Only MS features and tree location as input.

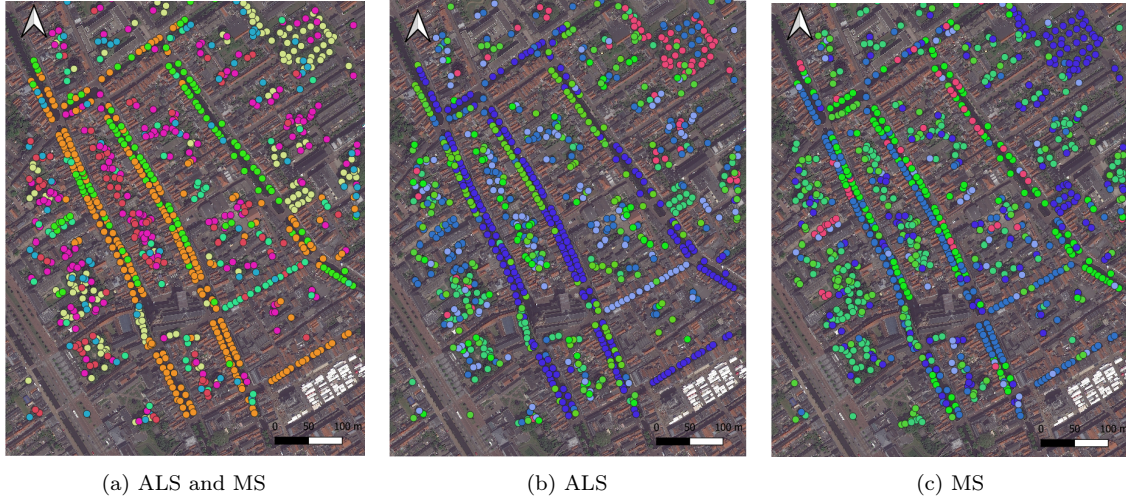


Figure 6.42: K-means clustering with $k=8$ for three scenarios: a) Combination of feature in put of ALS and MS, b) Only ALS features and tree location as input, c) Only MS features and tree location as input.

The difference between using both ALS and MS and using only ALS is small; however, the addition of MS helps in some areas to find similar tree species. Using only MS as input is not really applicable for identifying tree species or characteristics. In some areas, MS works well but only if the trees are very different, such as having specific colors or in regions with very dense vegetation. Both $k = 8$ and $k = 15$ show similar results in clustering trees along the streets, but $k = 15$ exhibits more variety in clusters of private trees.

Further only cases with $k=8$ and $k=15$ are evaluated focusing on the output computed using both ALS and MS inputs and only MS. The clustering results are evaluated using the tree species recorded in the Delft Municipality Tree Inventory as a reference to find different tree groups. Two main categories; clustering inconsistencies, and consistencies, are evaluated by analyzing different cases in Delft, Figure 6.43:

1. Clustering inconsistencies
 - (a) Case 1: Faulty Clustering
 - (b) Case 2: Faulty Clustering due to error in ITD
 - (c) Case 3: Trees different characteristics despite tree species label
2. Clustering consistencies
 - (a) Case 4: Detecting the same tree species in different locations
 - (b) Case 5: Detecting individual trees of the same species in different locations

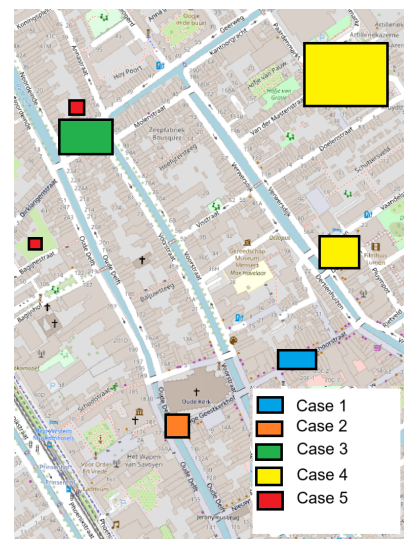


Figure 6.43: Locations of cases discussing clustering results.

6.6.1 Clustering Inconsistencies

There are inconsistencies between the tree species from the Delft Municipality Tree Inventory and the detected tree groups. Three main different scenarios are detected where inconsistencies occur:

1. The tree location is falsely detected (ITD did not perform well)
2. Trees are growing differently or are of different age and therefore appear very different although they have the same species
3. Trees are one species and can be identified as such visually but due to very odd growing pattern they are classified differently (Faulty in K-means clustering)

Case 1: Faulty Clustering

In some cases the clustering does not perform as expected. Along the Choorstraat in Delft are trees of the same tree species and age recorded in the Delft Municipality Tree Inventory, Figure 6.44a. This should be reflected in the clustering results. However, with both clustering cases $k=8$ or $k=15$ using ALS and MS features the trees are always separately grouped. Even when the input features are changed to only MS or only ALS this does not change.

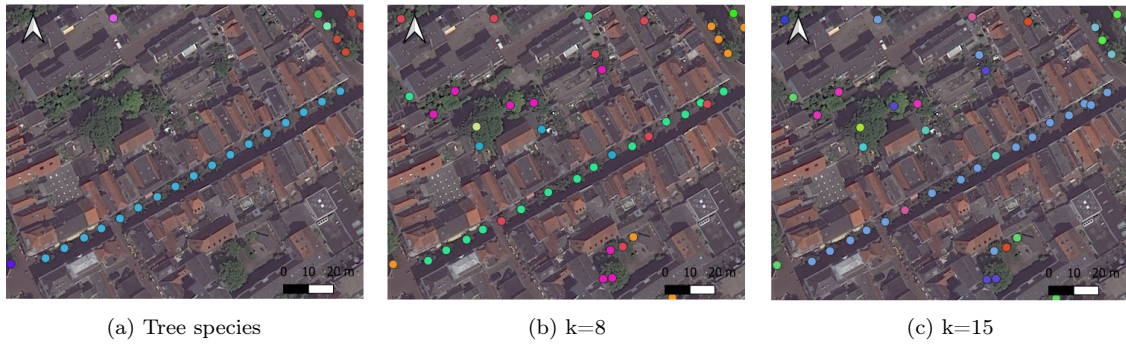


Figure 6.44: Tree species recorded in Delft Municipality Tree Inventory and K-means clustering using both ALS and MS features case 1, Location see Figure 6.43

When examining the trees in person, Figure 6.45a and 6.45b, the similarity between the trees can be seen. They have similar color and random structure. However, the randomness in structure and volume in the tree crown contributes to the clustering to show different tree groups. Despite the difference in appearance the trees are still similar to the extent that the expected result from the clustering should categorize these trees together.



(a) True image self-obtained 23.05.2024



(b) True image self-obtained 23.05.2024

Figure 6.45: True images showing case 1 of faulty clustering at location 1, Figure 6.43

A similar case of a tree that has the same species and appearance but is clustered apart can be seen in case 2 in the yellow section in Figure 6.46a. The most west tree in this section has very similar RGB and shape characteristics but there is a height difference, Figure 6.49a. The clustering here determines that difference in height out weighs the similarity in shape and color and therefore categorizes the tree differently then the next two.

These cases show that the clustering does not result in the desired outcome in some instances.

Case 2: Faulty Clustering Due to Error in ITD

The clustering results are also highly impacted by the ITD performance. If a tree is not correctly identified and rather either two trees are merged or one tree is segmented into multiple trees with the ITD the tree features are incorrect which can in turn result into faulty tree clustering.

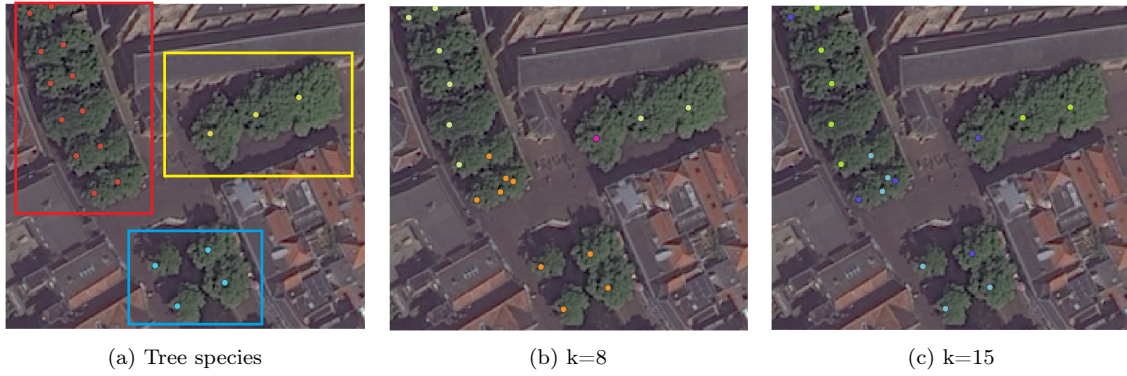


Figure 6.46: Tree species recorded in Delft Municipality Tree Inventory and K-means clustering using both ALS and MS features case 2, Location see Figure 6.43

One instance of faulty clustering due to faulty ITD is where a single tree was falsely segmented into three trees, Figure 6.46a showing the recorded tree species in the red box and Figure 6.46b showing the clustering result.



Figure 6.47: True images showing case 2 of faulty clustering, Location see Figure 6.43

Case 3: Different Tree Cluster While Identical Tree Species

The goal is to find similar trees in the urban environment. While the clustering result is now evaluated by comparing it to tree species recorded this does not always mean that the trees have similar characteristics.

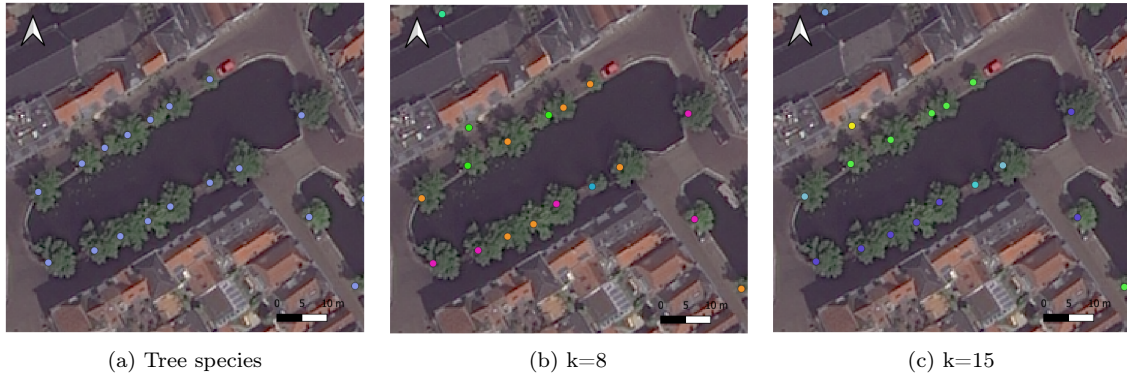


Figure 6.48: Tree species recorded in Delft Municipality Tree Inventory and K-means clustering using both ALS and MS features case 3, Location see Figure 6.43

While the Delft Municipality Tree Inventory labeled all trees as the same species, Figure 6.48a, the clustering shows that they are categorized into different groups, Figure 6.48b and 6.48c.



Figure 6.49: True images showing case 3 of faulty clustering, Location see Figure 6.43

During a manual inspection it can be noticed that the trees are all very different, Figure 6.49. The trees vary in geometric features such as tree height, crown shape, crown density, and structure, Figure 6.49b and 6.49c. In Figure 6.49a and 6.49a a difference in the color of the leaves can also be noticed. The same is true for trees in case 3 in the blue box in Figure 6.46a where the trees are of the same species but are of very different shape and color, Figure 6.47b. Grouping trees manually based on tree characteristics these trees would and should not be in the same category

which is represented in the clustering results. To evaluate urban tree influences based on the tree characteristics the grouping based on species is less relevant. Using unsupervised clustering the tree characteristics are grouped without input labels and only the geometric, reflectance and spectral features are considered.

6.6.2 Clustering Consistencies

Consistencies between tree the tree clustering and recorded tree species can be found. These consistencies can be detected on a larger scale where groups of trees in the same area are grouped together correctly based on species. Additionally, the clustering performance is promising when showing that similar tree groups in different areas are grouped together.

Case 4: Detecting the Same Tree Species in Different Locations

The clustering also shows where trees are similar in different locations this is true for trees that are recorded in the Delft Municipality Tree Inventory.

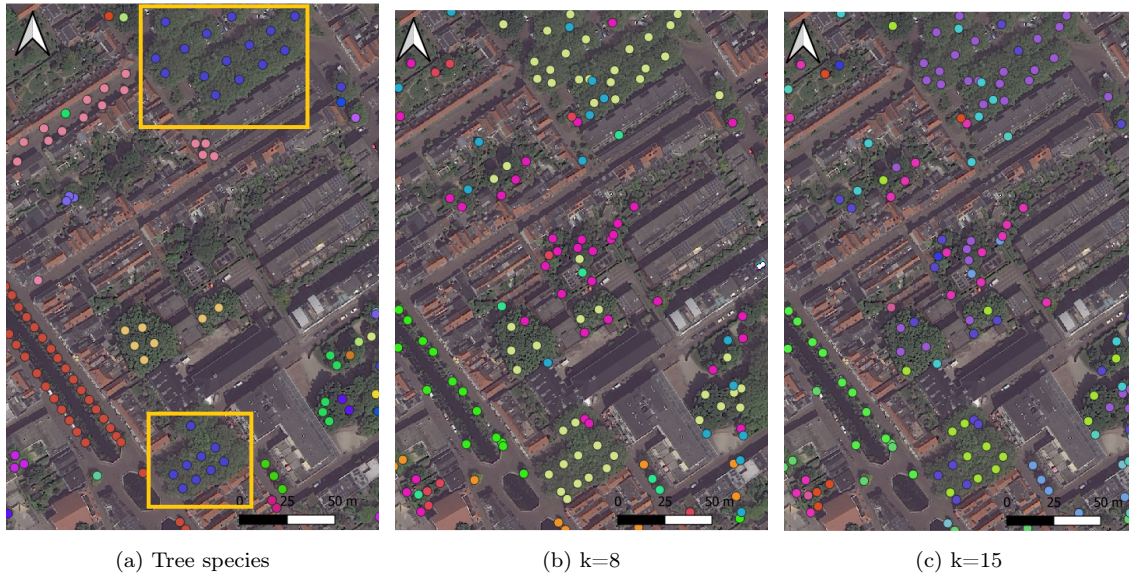


Figure 6.50: Tree species recorded in Delft Municipality Tree Inventory and K-means clustering using both ALS and MS features case 4, Location see Figure 6.43

Some groups of trees if detected correctly they are also clustered together representing one species. In Figure 6.50a the orange boxes show two locations where a group of trees have the same species. Using a smaller clustering number $k=8$ not only the group of trees can be detected as similar trees but also the similarity between the trees in these two locations is present, Figure 6.50b. While the tree similarity locally can be detected using $k=15$ the two locations are not grouped together, Figure 6.50c.

Case 5: Detecting Individual Trees of the Same Species in Different Locations

Rare individual trees can also be group together. This can be done in some cases more accurately then the Delft Municipality Tree Inventory. The ITD's tree location is more accurate as seen in Figure 6.51b. The same tree species is then also detected in a second location and they are grouped together, Figure 6.51d.

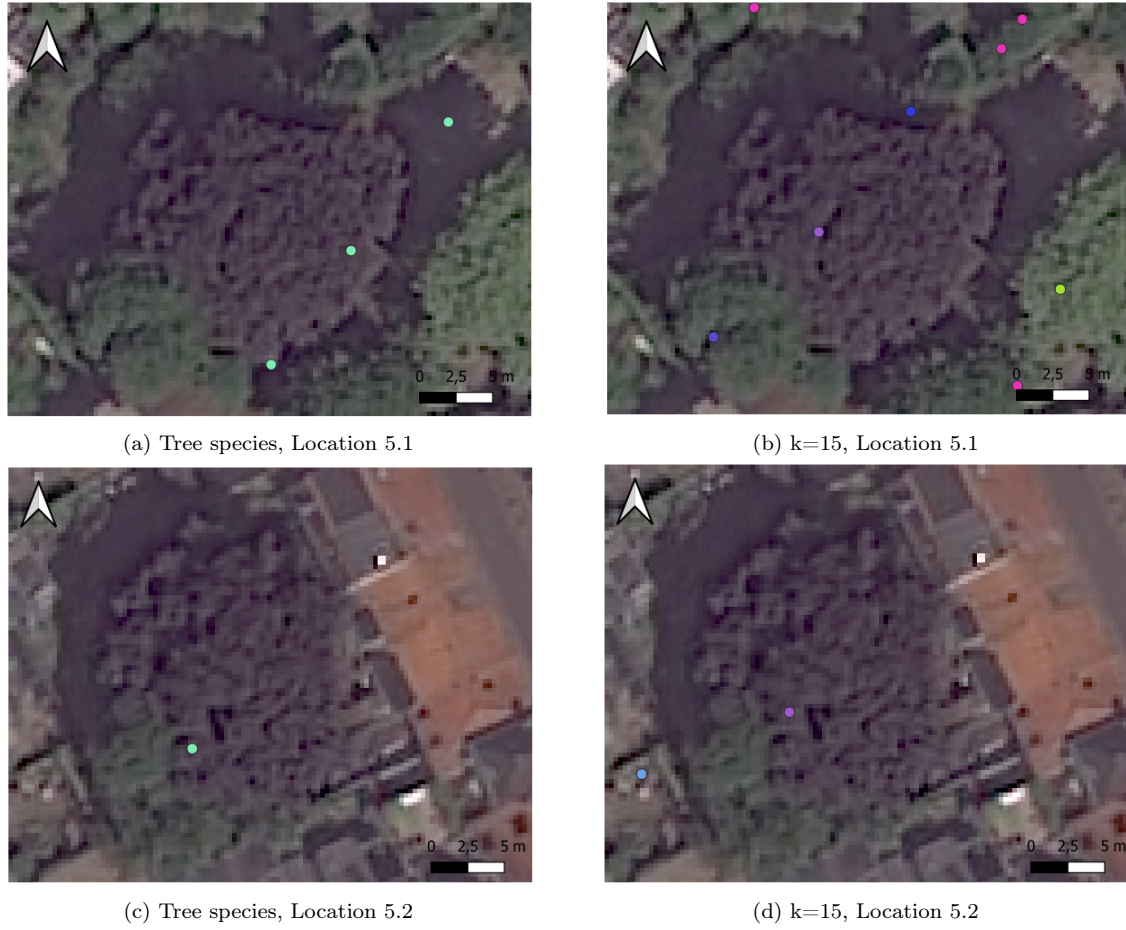


Figure 6.51: Tree species recorded in Delft Municipality Tree Inventory and K-means clustering using both ALS and MS features case 5, Location see Figure 6.43

6.7 Processing Tools, Efficiency and Scalability of the Method

The overall method can be segmented into the following processing stages:

1. Creating a training dataset for the Random Forest algorithm.
2. Building the Random Forest classification model.
3. Running the Random Forest classification on the dataset.
4. Individual tree detection.
5. Tree feature extraction.
6. Clustering.

The processes were implemented in both Python and C++. The Random Forest classification utilized the inbuilt function from Scikit-learn in Python ([Sklearn.ensemble](https://scikit-learn.org/stable/), n.d.). Individual tree detection was performed using the "Point-based Individual Tree Delineation from 3D LiDAR Point Cloud Data" method in C++ ([J. Wang, 2018](#)). Tree features were extracted using Python, and

the K-means clustering was also conducted in Python using an inbuilt function from Scikit-learn ([Sklearn.cluster](#), n.d.).

The relative processing time for these six segments is depicted in Figure 6.52.

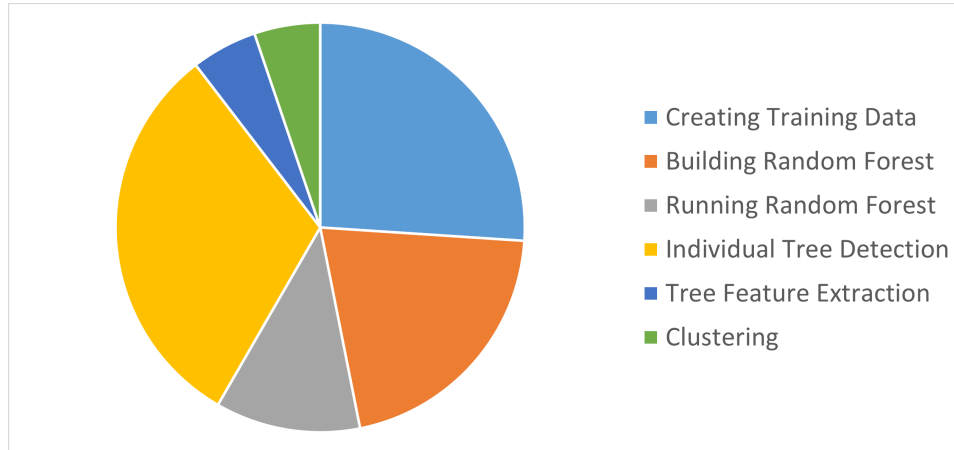


Figure 6.52: Pie chart of the relative processing time of the different processes.

Three main processes are particularly time-consuming:

1. **Individual Tree Detection:** This is the most time-consuming step, influenced by the number of points, point density, and model parameters. Larger search radii and finer vertical resolutions significantly increase processing time. Scaling this step up to larger areas will further increase processing time, particularly in areas with high point density. On an 8-core laptop, processing 1,230,473 points took 1256 minutes. Larger datasets, especially those with higher point density, significantly slowed down the process, occasionally exceeding available memory and causing crashes. Consequently, the study area was reduced to 500x600 meters.

2. **Creating the Training Dataset:** This step is performed manually to ensure the Random Forest model is well-trained. For the Delft urban area, creating the training dataset took approximately 10 hours over multiple days. A comprehensive training dataset is necessary to include a variety of data covering different trees and non-tree points. For broader applications, such as covering all of the Netherlands, this step could become significantly more time-consuming due to the need for a more diverse training dataset.

3. **Building the Random Forest Model:** As the training dataset grows in size, constructing the Random Forest model becomes the third most time-consuming step. With a training dataset of 5,897,528 points, building the model took 146 minutes on an 8-core laptop.

The least time-consuming processes are tree feature extraction and clustering. The duration of tree feature extraction depends on the number of trees, while the K-means clustering time is influenced by the number of observations, features, iterations, and clusters. As these processes are scaled up, they will become more time-consuming, potentially altering their relative processing times compared to other steps.

Using a more powerful processing PC with more memory can reduce processing time and allow for larger datasets to be processed more efficiently.

7 Discussion

Throughout the research some results are highlighted and discussed. The tree segmentation using Random Forest classification vs. filtering using geometric features is discussed. Further, the chosen method and results are compared to other research. With the Individual Tree Detection (ITD) method the settings and their implications are discussed. Tree features detected and implemented in this research are compared to others. Then the clustering results are discussed in regard to their settings, limitations, and utility. Lastly, the recommendations and potential enhancements are discussed.

7.1 Tree Classification

Random Forest is a powerful classification technique that, in this setup, considers factors like height, intensity, number of returns, and return number to build its model. Including height significantly impacts the classification results, likely due to the training data consisting of taller trees and lower non-tree points. Without height, the model’s accuracy decreases. Although the data is colorized, these colors are not used in the classification. The AHN4 colored data uses airborne images, causing points beneath the canopy to be colored similarly to the top. Misalignment of images and points results in color bleeding at structure edges, causing some trees to be colored based on nearby structures, as shown in Figure ??.

While constructing the RF model can be time-consuming due to the complexity of selecting and evaluating numerous decision trees, once the model is built, classification with RF is relatively fast. However, RF’s effectiveness is based upon the quality and relevance of the training data. For each new environment, it is necessary to create new training data to ensure the model can accurately classify new tree species or conditions, which can be a labor-intensive process. Creating training data for Random Forest (RF) models is often a manual process, which is not only time-consuming but also prone to errors. This manual intervention in dataset preparation can introduce inconsistencies and inaccuracies, impacting the reliability and performance of the RF model in tree segmentation tasks.

On the other hand, another method to classify trees by computing geometric features for tree classification, although time-consuming, especially with varying voxel sizes, offers a flexible approach applicable in diverse environments. This method’s speed post-computation and adaptability make it attractive for broad applications. However, the reliance on manual selection for filtering points can introduce errors and variability, potentially affecting the dataset’s consistency.

In conclusion, if a comprehensive and well-curated training dataset is available, RF can provide effective tree segmentation. Otherwise, exploiting geometric features for point filtering may offer less time consuming alternative, although with considerations for potential manual selection errors.

In other research trees can also be detected using unsupervised segmentation methods using either the LiDAR or spectral data. This method avoids the limitations introduced by the difficulties and errors in the training data (Holmgren et al., 2008; Li et al., 2020). Geometric parameters extracted from LiDAR data have been adapted to different environments and are used for tree detection with a similar runtime of supervised classification methods (Marrs & Ni-Meister, 2019; Secord & Zakhori, 2007). However, this proved to be less accurate in this study.

Moreover, using spectral imagery, trees are usually detected by extracting polygons represent-

ing tree crowns, although distinguishing between trees and other vegetation like bushes can be challenging, particularly in dense forest environments (Itakura & Hosoi, 2019; Boom Register, 2018). This method proves more efficient in open or homogeneously forested areas (Kukunda et al., 2018). High-resolution airborne imagery, with details as fine as 15 cm, significantly enhances tree detection accuracy, making it particularly useful in precision forestry and urban landscape management (Holmgren et al., 2008).

While in this research the Delft Municipality Tree Inventory is not implemented as input data but rather as validation, other research utilize tree inventories to either classify vast tree species (Niedzielko et al., 2024) or focus on a specific number of trees (Hartling et al., 2019). In scenarios where a complete tree inventory is available or only specific trees need evaluation, point growing algorithms for LiDAR and region growing for multispectral imagery provide effective methods to isolate tree points or regions (Itakura & Hosoi, 2019). The integration of LiDAR with multispectral data using machine learning techniques like neural networks and support vector machines has shown improved classification accuracies, highlighting the value of combining spectral and structural data for enhanced tree species classification (Marrs & Ni-Meister, 2019; Chi et al., 2021).

7.2 Individual Tree Detection

In Delft there is a large variety of trees: small and young trees, big and old trees, heavily managed and unmanaged trees, single standing trees and dense clusters of trees. The ITD (Individual Tree Detection) has to be adjusted so that for all different trees the best possible results can be found. The search radius was selected to be 1.5m, Table 5.2. When changing the radius to a smaller value, the algorithm can distinguish easier between very dense growing trees. However, big trees are then often separated in multiple small trees. With a larger search radius very large trees with difficult structures in the tree crown can be correctly classified as a single tree. But this results in dense tree clusters to be classified as one big tree. Furthermore a larger search radius also increases the processing time of the algorithm. The vertical resolution was chosen to be 1m. This parameter is also dependent on the point density which as discussed varies in the dataset. The vertical resolution determines the voxel step sizes that the algorithm takes to determine which point belongs to which tree. With single standing trees this parameter is less important. With dense tree clusters this parameter determines the fineness of the result. When choosing a smaller value the processing time increases and the results might be more accurate in distinguishing where trees intercept. However, this is very difficult to validate. More important then assigning each point to the right tree is to make sure that the tree peak/ initial point is found. Therefore, to still ensure a reasonable processing time the search radius was increased as well as the vertical resolution to compensate. Lastly the minimum number of clusters is chosen to be 10. Small clusters such as street furniture that was not removed with the RF classification is filtered out.

7.3 Tree Features

Many different Tree Features can be computed. In other studies different additional tree features are extracted and used to classify trees using spectral and LiDAR data. In the research from Niedzielko et al. (2024) similar tree features are extracted from the ALS. However, many more spectral features were computed since they had more band available from hyper spectral images. They have up to 51 different tree features. The spectral data utilised in this study has a very high number of spectral bands (430 in the case of utilised data) (Niedzielko et al., 2024). Therefore

they were able to find many additional spectral features. In comparison in this research the main driving features are from the ALS data and new computed geometric features such as sphericity were utilized which other research is not implementing.

7.4 Clustering

Most research shows urban tree classification using either spectral or airborne LiDAR data. Some research such as discussed by [Shen & Cao \(2017\)](#) shows the benefit of combining the data. In most studies using either single or combined data sets, tree classification is typically performed using a supervised classification method. This method often relies on either a smaller sample of specific trees or a large-scale tree feature inventory ([Niedzielko et al., 2024](#)). In this study the unsupervised clustering performs best using ALS and MS together provides the best results, while using only MS yields the lowest performance. ALS alone also shows quite promising results. However, if long-term growth and seasonality are to be evaluated, the MS information can be quite valuable. Other research also shows the importance of adding MS to the tree features.

While the clustering shows promising results it also has limitations. Limitations include the challenge of up-scaling, which can be problematic with finding the right k if a larger variety of trees are in the dataset. However, finding tree species is not the ideal goal to determine the tree influence in the city. For this purpose, a smaller k can be used, allowing similar trees to be grouped so their influence can be evaluated. If the goal is to identify tree species on a larger scale with a large number of different trees, a supervised classification method is advised. For example, using the Delft tree inventory to label the detected trees to create training data and then classifying the private trees based on that would be an effective method. However, established trees within one species show very varying growth patterns, shapes, and colors due to age, environmental, and human influences. These differences will make it difficult to create a base pattern for the tree species in the training data. Another limitation of this tree grouping method is the error propagation. The clustering results are highly dependent on the performance of Random Forest (RF) classification and Individual Tree Detection (ITD). Errors in RF classification can propagate and affect the accuracy of ITD, leading to incorrect identification of tree features. When tree features are not correctly determined, the clustering process suffers, resulting in misgrouping of tree species. Conversely, when tree features are accurately identified, the clustering outcomes demonstrate that similar tree species can be effectively grouped together. Thus, the effectiveness of clustering is based upon the accuracy of both RF and ITD processes.

Only geometric, reflectance, and spectral features are considered in the unsupervised clustering, meaning trees are grouped based on these characteristics. These characteristics are important in understanding the trees' impact on the urban environment. The tree shape and size influence the trees' effect on the wind pattern in the city. The crown shape and density influence temperature regulation, affecting the urban heat island impact. Lastly, the spectral information gives insight into the trees' health and seasonality. All these tree features are also important when evaluating urban trees' ecological and aesthetic impacts.

7.5 Potential Tree Classification Enhancements and Recommendation

In the future the tree classification methods can be modified to improve the workflow, validation and implication of the research. Enhancements for future tree classification methodologies could include:

- **Improving Tree Classification:** To reduce propagating errors the tree classification could be improved. This could be done in multiple ways such as improving/ expanding the training data, implementing other classification methods, combining spectral and LiDAR data before tree classification to have more input information.
- **Expanding multispectral Data Utilization:** Utilizing multispectral imagery with a wider array of bands to extract detailed information about vegetation properties, including RGB and NDVI data from entire tree crowns. This could provide deeper insights into tree health and stress levels, which are critical for effective tree management.
- **Temporal Changes Monitoring:** Engaging in long-term research to observe temporal changes in tree populations would aid in understanding their growth patterns and the impacts of environmental changes over time. These can further be correlated to environmental or climate changes to analyze their effect on tree health and growth.
- **Extensive Field Validation:** Enhancing data accuracy through more comprehensive field-work for validation purposes is essential. This helps ensure that tree classification outputs are reliably correlated with actual ground-truth data. This is especially relevant for trees excluded from the tree inventory.
- **Utilizing Existing Tree Inventories:** Integrating findings and methodologies from established research like the Delft Tree Symposium can serve as a robust validation tool, enhancing the credibility and applicability of tree classification methodologies. In the future this research will provide a more detailed tree inventory that can be utilized as validation data or can be used as input data to for either tree detection or to classify trees using supervised classification. Currently the tree inventory has limitations and false or missing information therefore using it as training data for supervised classification is not advised.
- **Cross-City Evaluations:** Testing and refining tree classification methodologies across different cities will help determine how this workflow perform under varying urban environmental conditions. In the future, by implementing and adjusting the workflow a tree classification technique could be developed to classify urban and potentially rural trees in the entire Netherlands.
- **Adaptive ITD Parameters:** Adjusting the ITD to accommodate the specific characteristics of the tree environments under analysis is crucial. This involves not only refining technical settings like the search radius but also integrating broader ecological and environmental factors that influence tree growth, such as adjacent vegetation, human activities, and other relevant environmental factors. Implementing adjustable parameters that respond to variations in tree crown density and point data within specific regions can improve differentiation between trees of different ages and crown densities, thereby enhancing detection accuracy.

Incorporating these enhancements into future tree classification research will not only improve the precision and reliability of tree classification but also significantly contribute to more effective management and conservation practices in both urban and natural landscapes. By considering both technological advancements and environmental insights, future research can lead to more precise and ecologically attuned applications in the field of remote sensing and landscape management.

8 Conclusion and Recommendations

This conclusion chapter addresses the main research question: To what extent can urban tree characteristics be identified from airborne LiDAR and spectral satellite data using machine learning? The answers to the subquestions explored throughout this study are summarized.

8.1 Relevance of Urban Tree Characteristics

What tree groups in urban areas should be characterized, and what are the ecological, aesthetic, and urban planning factors driving their relevance?

Urban tree monitoring should encompass a variety of characteristics, including height, crown geometry, color, species, age, and health. These attributes are critical for ecological understanding, enhancing aesthetics, and effective urban planning. Tree height affects microclimates and energy consumption in nearby buildings, while crown geometry influences shading, CO₂ absorption, and urban climate regulation. Tree color provides aesthetic value and indicates health. Species identification helps manage infrastructure risks and allergen impacts, while maintaining biodiversity. Tree age insights contribute to lifecycle understanding and resilience. Monitoring tree health predicts disease outbreaks and assesses environmental stressors.

Grouping trees based on these characteristics offers deeper insights into urban biodiversity, ecological dynamics, and urban planning. It allows for evaluating the influence of trees on urban factors such as wind, temperature, and aesthetics, while also understanding how the urban environment impacts tree health and growth. Additionally, the urban environment can significantly impact trees. By correlating these tree characteristics to their environment, crucial insights can be gained into how future urban planning can ensure trees thrive. This helps identify which trees will thrive in specific environments, aiding in the development of more resilient and sustainable urban green spaces.

8.2 Extraction of Tree Location from AHN4

How to extract tree location from airborne LiDAR and the spectral data?

The first crucial step in classifying trees from LiDAR was to identify the tree points. Two methods were evaluated in this study: supervised classification method Random Forest (RF) and filtering based on computed geometric features. The supervised classification method performed better with 92.66% and 88.43% accuracy, while the geometric features method resulted in an accuracy of 65.73% and 54.78% for the two evaluated areas. However, both accuracy's depict only true positives as the testing data is limited to only tree points that were manually selected. Using the RF result the data was segmented further to differentiate between different trees applying the Individual Tree Detection (ITD) algorithm (J. Wang, 2018). The parameters driving the algorithm are adapted to the study area, however due to the variety in tree densities, heights, growth pattern, and ages the parameters can not account for all circumstances. This results in some limitations. There are four main limitations, listed from least to most important: 1) trees are not detected at all, 2) a single tree is identified as multiple trees, 3) multiple trees are identified as single tree, 4) Falsely detected tree. These limitation are attributed to the limitations in the training data used in the RF model that removes small/young trees as well as the parameters set

in the ITD. While there are some limitations, 69.58% of trees recorded in the Delft tree inventory are detected correctly within a 2.5m radius. The mean location difference between the recorded tree locations in the Delft tree inventory and the detected trees is 0.71m. Furthermore, in the study area 460 additional trees are detected that are not recorded in the inventory. These detected trees are private trees and provide great additional information in the vegetation distribution in this urban environment.

The method of urban tree detection using airborne LiDAR point cloud and Random Forest classification presents both advantages and limitations. One of the primary limitations is error propagation, primarily stemming from tree classification inaccuracies using AHN data. However, significant reduction in detection errors can be achieved by refining the tree classification process from AHN datasets. Additionally, adapting ITD parameters to specific locations could mitigate errors caused by the heterogeneous nature of urban trees, thereby improving overall accuracy.

A key advantage of this method is its scalability. Once a comprehensive training dataset is established, the method can be scaled up to cover larger areas. This scalability is complemented by relatively fast processing times, facilitating efficient data collection and analysis across extensive urban landscapes.

Moreover, scaling up this approach could establish a standardized method for tree detection across the Netherlands, ensuring consistency in urban tree inventories across different cities. This uniformity not only streamlines urban planning and management but also supports broader initiatives in urban forestry and biodiversity conservation.

8.3 **Extracted Tree Characteristics**

What relevant tree characteristics can be retrieved from airborne LiDAR and spectral satellite data?

Different tree features are extracted from individual trees using both LiDAR and spectral data. In total 50 different tree features are computed. The extracted features from the LiDAR data are geometric and reflectance features. The reflectance features are extracted from the intensity values. The geometric features include the point density, count and height distribution. The height found of the detected trees is validated using the height estimation recorded for some trees in the Delft tree inventory. The mean height difference is around 2.6m. One of the valuable aspects of this research is the use of geometric features like tree sphericity, which can offer insights into urban wind flow patterns. However, it's important to note that the sphericity measurements, derived from LiDAR data collected during the leaf-off season, may not fully capture the trees' characteristics throughout the year. Additionally, a correlation between the point density and the maximum height as well as sphericity was detected. This shows that dense and large trees have higher sphericity values.

Spectral features extracted from high resolution, 30cm, spectral satellite images from four different time periods spanning: spring, late spring, summer and fall of 2013, include RGB, NIR and NDVI values. The wider spread of RGB values and lower NDVI during spring suggest that not all trees have foliage or trees might have flowers. In late spring the trees are showing a much higher NDVI indicating a healthy tree canopy in the city. The NDVI then reduces in summer likely due to lack of precipitation in 2023, which could differ from year to year. In fall the mean NDVI is very similar to summer. However, here the standard deviation is higher indicating some trees increased

in NDVI while others reduced.

Tree height distribution, crown sphericity, RGB color, and other geometric, reflectance, and spectral features are crucial for urban tree monitoring for several reasons. These features provide comprehensive insights into urban tree characteristics and health. Tree height distribution helps understand spatial distribution and growth patterns, essential for urban planning and management. Crown sphericity indicates tree shape and can influence urban wind flow and aesthetics. RGB and color data offer seasonal and health-related information, aiding in assessing foliage density, stress levels, and overall vitality. Together, these features enable a holistic approach to urban tree monitoring, supporting biodiversity assessment, environmental impact evaluation, and sustainable urban development strategies.

This study shows that current tree inventories can be expanded with additional geometric, reflectance and spectral features. The ALS (Airborne Laser Scanning) features can aid in the mapping of geometric features of trees such as tree heights, density or shape. On the other hand the MS (Multispectral) features can indicate tree seasonality and health.

8.4 Clustering Urban Trees

How does the combination of tree features from LiDAR and spectral satellite data drive the tree characterization?

Using K-means clustering with different input and cluster numbers showed that the best results are achieved when both ALS and MS tree features are used, particularly with smaller cluster numbers such as $k = 8$ and $k = 15$. However, inconsistencies in the clustering outcomes can be attributed to several factors. First, tree location may be falsely detected if the ITD method does not perform well, leading to incorrect tree features such as height, sphericity, and RGB values. Second, trees of the same species may grow differently or be of different ages, resulting in significant variations in their appearance. This variability, while seemingly disadvantageous, can actually enhance clustering by incorporating a broader range of characteristics such as shape, height, and growth patterns. Third, trees with unusual growth patterns may be misclassified despite being visually identifiable as the same species. Although some groups easily detected manually are not identified using this method, the overall results yield promising implications. ITD demonstrates high accuracy, adding crucial information such as the locations of private trees, and tree characteristics can be computed automatically for inaccessible trees, allowing their grouping with similar trees. This supports urban tree biodiversity evaluation, environmental impact assessment, and aesthetic planning by grouping trees with similar characteristics, thereby aiding efficient analysis and management of urban forests.

8.5 Utility

What is the practical utility of the tree characterizations?

This research incorporated additional tree features such as sphericity, tree height distribution, and seasonal variability in RGB and NDVI. These additions are crucial for advancing future research on tree influences and monitoring tree health. The practical use of the tree characterizations identified in this research lies in their ability to offer a more nuanced understanding of urban trees and their interactions with the environment. By encompassing dimensions like tree height, crown

geometry, tree color, species, age, health, sphericity, tree height distribution, and seasonal variability in RGB and NDVI, this research surpasses conventional species identification approaches. These characterizations are particularly significant as they provide insights into urban biodiversity, microclimate regulation, and energy consumption. For instance, the tree crown geometry impact shading and CO₂ absorption, influencing urban climate regulation and local thermal comfort. Tree color and spectral features indicate health and photosynthetic activity, essential for assessing the quality of urban green spaces.

This method enables a comprehensive analysis of how trees affect and are affected by their urban environment. Grouping trees based on these features allows researchers to evaluate their influence on factors such as wind and temperature, contributing to more effective urban planning and ecological resilience. The approach also facilitates long-term monitoring of urban forests, revealing temporal changes in tree growth patterns and overall health. By correlating these features with environmental factors, future research can predict how trees will respond to urban development, climate change, and ecological dynamics.

8.6 Recommendation

To enhance the accuracy and applicability of these characterizations, several recommendations are proposed. Improving tree classification algorithms and incorporating more detailed data can refine the results. Expanding the use of high-resolution multispectral images can capture seasonal changes more accurately, providing better health assessments. Reapplying this workflow over time will allow for continuous monitoring of tree growth and health, offering valuable long-term data. Extensive fieldwork is necessary to validate automated methods and ensure their reliability.

Integrating this method with existing urban tree inventories can create more comprehensive and up-to-date datasets, enhancing urban green space management. Applying this methodology across different cities can provide insights into urban tree diversity on a larger scale, helping develop universal urban forestry strategies. Continuously adapting Individual Tree Detection (ITD) parameters will improve detection accuracy for various urban environments and tree types. Implementing these recommendations will enable cities to manage their green spaces more effectively, enhance ecological resilience, and plan for future environmental challenges. This research underscores the importance of detailed, automated tree monitoring for creating sustainable and resilient urban landscapes, facilitating further study of the complex interactions between urban trees and their environments.

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A Appendix

A.1 Satellite Imagery

Year	Season	Resolution [cm]	Bands	Usability	Note
2023	Nov/Dec/Jan	30	RGB		Clouds covering Delft
2023	Sep/ Oct	30	RGB	x	No clouds visible
2023	July/ August	30	RGB	x	No clouds visible
2023	June/July	30	RGB		Clouds covering Delft
2023	April/May	30	RGB	x	No clouds visible
2023	March/April	30	RGB	x	No clouds visible
2022	Nov/Dec/Jan	50	RGB		Clouds covering Delft
2022	Sep/ Oct	50	RGB	x	No clouds visible
2022	July/ August	50	RGB	x	No clouds visible
2022	June/July	50	RGB		Clouds covering Delft
2022	April/ May	50	RGB	x	No clouds visible
2022	March/ April	50	RGB	x	No clouds visible
2021	Nov/Dec/Jan	50	RGB		Clouds covering Delft
2021	Sep/ Oct	50	RGB	x	No clouds visible
2021	July/ August	50	RGB		Clouds covering Delft
2021	June/July	50	RGB	x	No clouds visible
2021	April/ May	50	RGB	x	No clouds visible
2021	March/ April	50	RGB	x	No clouds visible
2020	Nov/Dec/Jan	50	RGB		Clouds covering Delft
2020	Sep/ Oct	50	RGB	x	No clouds visible
2020	July/ August	50	RGB	x	No clouds visible
2020	June/July	50	RGB	x	No clouds visible
2020	April/ May	50	RGB		Clouds covering Delft
2020	March/ April	50	RGB		Extremely saturated
2019	Nov/Dec/Jan	50	RGB		Low saturation
2019	Sep/ Oct	50	RGB		High saturation
2019	July/ August	50	RGB	x	No clouds visible
2019	June/July	50	RGB	x	No clouds visible
2019	April/ May	50	RGB	x	No clouds visible
2019	March/ April	50	RGB	x	No clouds visible

Table A.1: Availability and usability of high resolution satellite imagery from NSO

A.2 Delft Municipality Tree Inventory

A.2.1 Data Description

Attribute	Description
X, Y	Geographical coordinates of the tree's location.
Type	General category of the vegetation. In this case all data entries are categorized as trees.
Element Number	Unique identifier for tracking and management purposes.
Management Group	Distinguishing trees into the following groups: non-free growing tree, topiary tree, free growing tree, tree to be determined, fruit tree, ecologically managed tree.
Planting Year	Year the tree was planted.
Tree Species	Specific species of the tree
Tree Status	Description of tree status in regards to tree development. Distinguishing between monumental and newly planted trees.
Branch Free Zone	Description of the intrusion of branches on a set branch free zone, if applicable.
Environmental Risk Classes	Categorization based on potential risks to or from the tree. distinguishing between three groups: general, increased, and limited.
Ambition Level	Intended or expected growth and development targets for the tree. With four different levels: C (moderate) to R-(sober), B (sufficient) to R (basic), A (good) to R+ (good), and A+ (very good) to R++ (excellent).
Height	Current height of the tree, critical for urban forestry management. The height, if provided, is given in a range. There are seven different height ranges in which the trees are categorized; <6m, 6-9m, 9-12m, 12-15m, 15-18m, 18-24m, and >24m.
Diameter	Diameter of the tree trunk, typically measured at breast height. Not available for most trees.
Location	Descriptive detail about the tree's location. Indicating the ground conditions of the tree location.
Administrator	Individual or entity responsible for the tree's administrative management.
Owner	Legal owner of the tree (e.g., municipal government, private entity).
Extra Information 2 & 3	Additional data about the tree not covered in other categories. The provided information is not further explained.
Green Area Code	Code linking the tree to a specific green space or park within the urban area.
Green Area Name	Name of the green space or park where the tree is located.
Municipality	Detailing in which municipality the tree is located.
Neighborhood	Giving a general indication in the tree location within the municipality.
District	The city district where the tree is located.
Placement	Placement of tree. Only one type recorded: within built-up areas.

Table A.2: Description of the Delft Municipality Tree Inventory

Scientific Name	Common Name
<i>Tilia x europaea</i>	Common Lime
<i>Ulmus x hollandica</i> 'Groeneveld'	Dutch Elm 'Groeneveld'
<i>Aesculus hippocastanum</i>	Horse Chestnut
<i>Pyrus calleryana</i> 'Chanticleer'	Callery Pear 'Chanticleer'
<i>Populus x canadensis</i>	Hybrid Poplar
<i>Alnus x spaethii</i> 'Spaeth'	Spaeth Alder
<i>Tilia x europaea</i> 'Euchlora'	European Linden 'Euchlora'
<i>Ulmus x hollandica</i> cv.	Dutch Elm cultivar
<i>Populus x canadensis</i> cv.	Canadian Poplar cultivar
<i>Aesculus hippocastanum</i> 'Baumannii'	Baumann Horse Chestnut
<i>Tilia platyphyllos</i> 'Delft'	Large-leaved Lime 'Delft'
<i>Crataegus monogyna</i>	Common Hawthorn
<i>Acer platanoides</i>	Norway Maple
<i>Betula pendula</i>	Silver Birch
<i>Liquidambar styraciflua</i>	Sweetgum
<i>Tilia cordata</i>	Small-leaved Lime
<i>Acer saccharinum</i>	Silver Maple
<i>Ulmus x hollandica</i> 'Commelin'	Dutch Elm 'Commelin'
<i>Prunus avium</i>	Wild Cherry
<i>Sorbus intermedia</i>	Swedish Whitebeam
<i>Populus nigra</i> 'Italica'	Lombardy Poplar
<i>Tilia x europaea</i> 'Zwarte Linde'	European Linden 'Black Linden'
<i>Robinia pseudoacacia</i>	Black Locust
<i>Ulmus</i> 'Lobel'	Elm 'Lobel'
<i>Prunus serrulata</i> 'Kanzan'	Japanese Cherry 'Kanzan'
<i>Prunus serrulata</i> cv.	Japanese Cherry cultivar
<i>Acer campestre</i> 'Elsrijk'	Field Maple 'Elsrijk'
<i>Ulmus x hollandica</i>	Dutch Elm
<i>Ulmus</i> 'Plantijn'	Elm 'Plantijn'

Table A.3: Scientific and common names of most occurring trees in the Delft Municipality Tree Inventory.

Trees	Number of trees recorded by the municipality in Delft	Image ((den Berk Nurseries, n.d.))
Platanus x hispanica	2120	
Fraxinus excelsior	2346	
Salix alba	1896	
Unknown	1972	
Ulmus x hollandica 'Vegeta'	1227	

Trees	Number of trees recorded by the municipality in Delft	Image
Acer pseudoplatanus	1178	
Tilia x europaea 'Koningslinde'	951	
Acer campestre	881	
Alnus glutinosa	895	

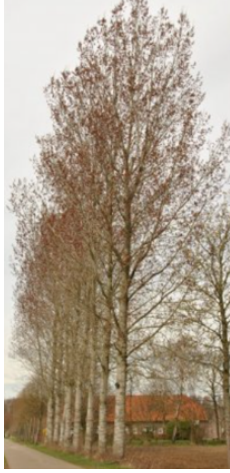
Trees	Number of trees recorded by the municipality in Delft	Image
Populus x canadensis 'Robusta'	866	
Sum of sample	14332	35%
Sum of all	35398	

Table A.4: Images and count of the top 10 most common tree species recorded by the municipality in Delft along with their images. All tree images are from [den Berk Nurseries](#) (n.d.).

A.2.2 Further Data Visualization

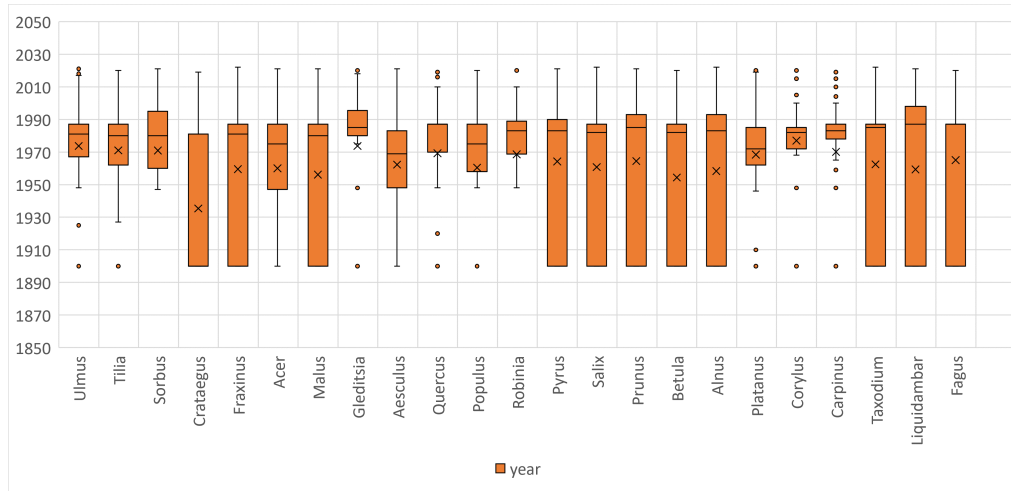


Figure A1: Tree Ages Histogram from the Delft Municipality Tree Inventory with more than 100 counts

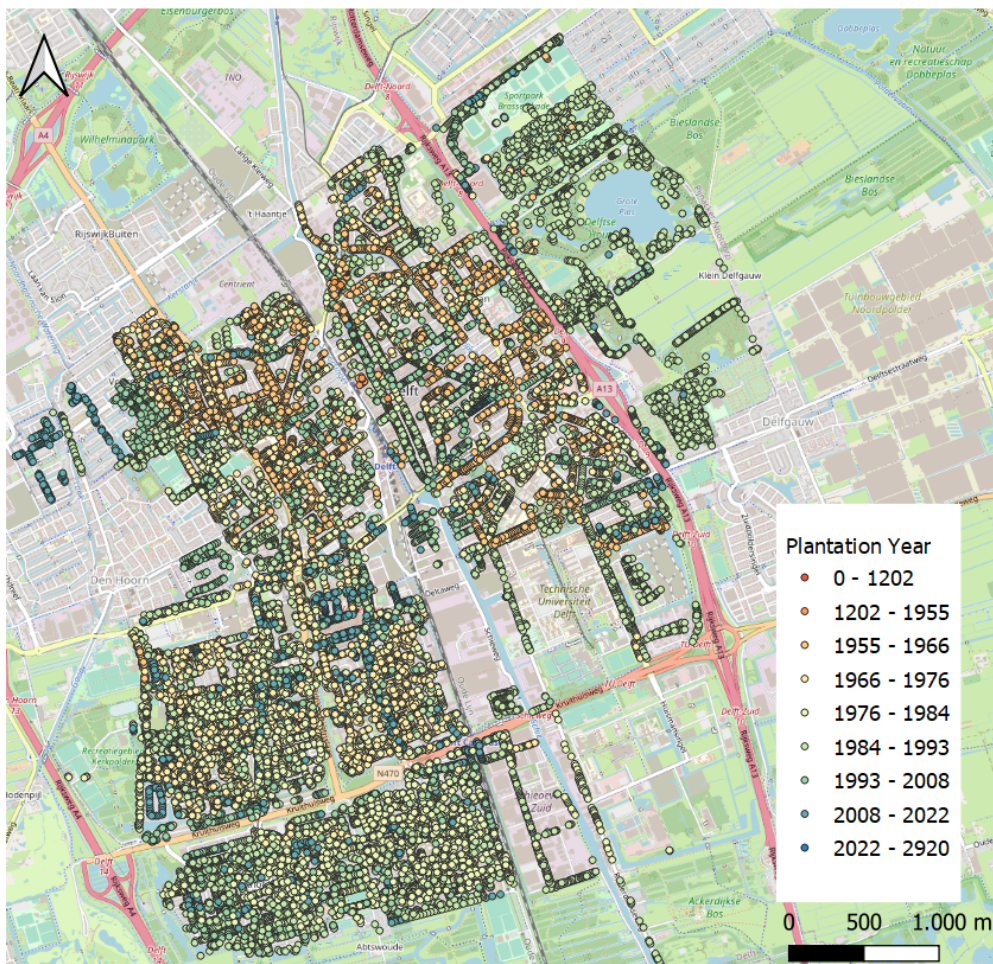


Figure A2: Map of Tree Ages from the Delft Municipality Tree Inventory

A.3 Colorized AHN4

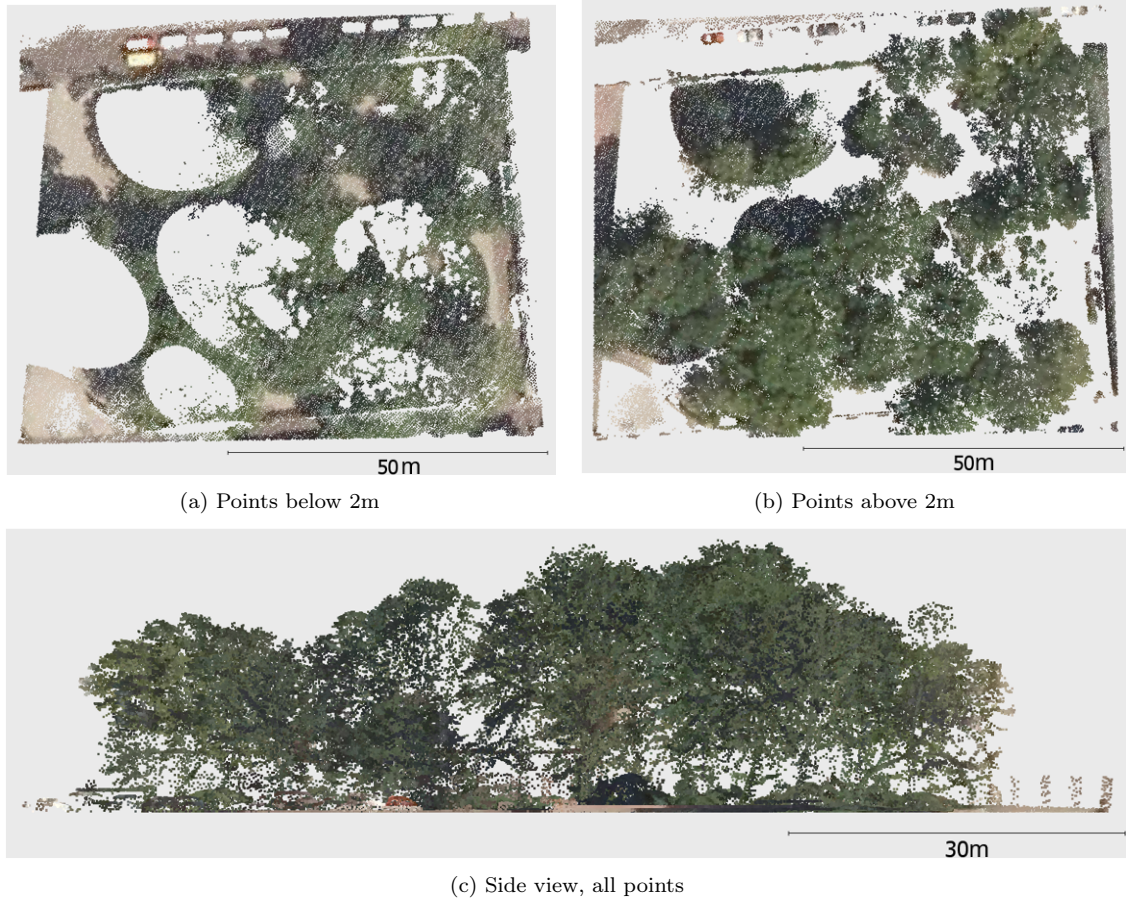


Figure A3: AHN4 colorized images from aerial imagery

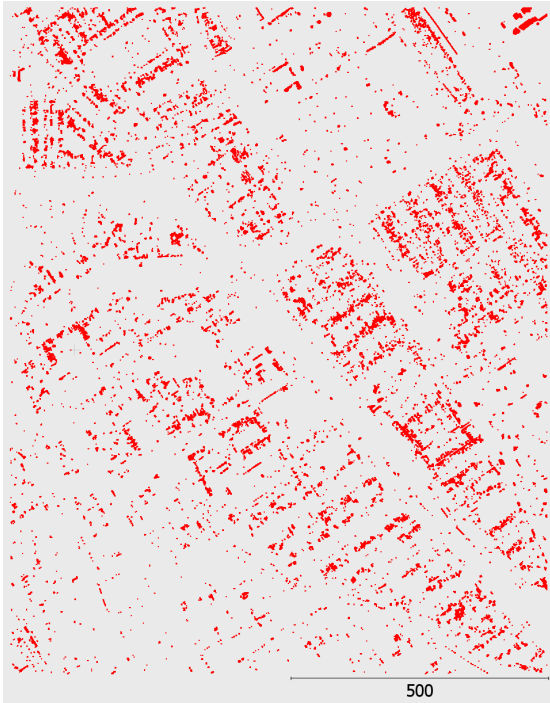


Figure A4: AHN4 colorized images from aerial imagery, larger points showing points above 2m and smaller points showing points below 2m.

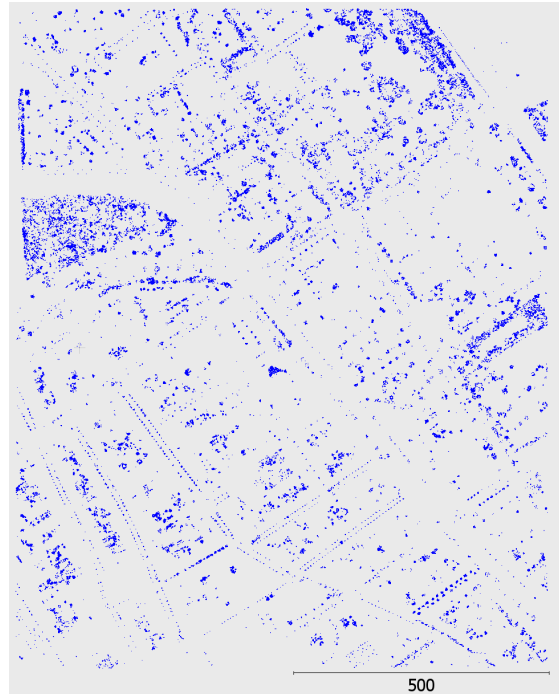
A.4 Random Forest Classification



(a) Random Forest classification result for classifying trees, in blue in Figure 6.2



(b) Random Forest classification result for classifying non trees, in green in Figure 6.2

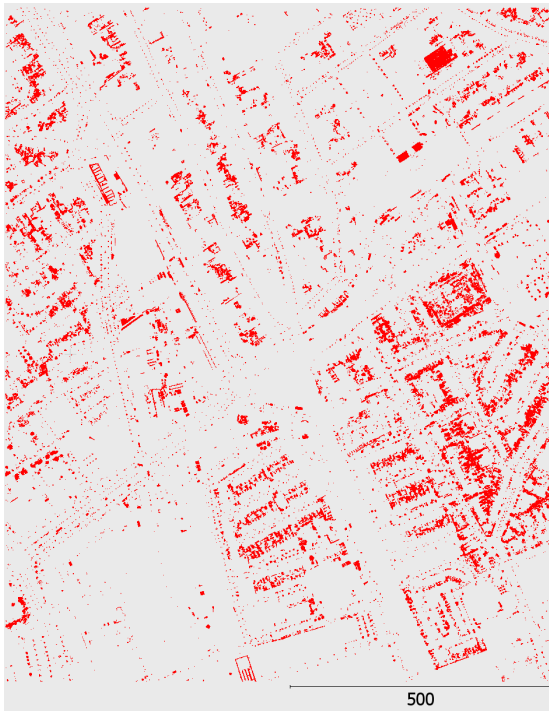


(c) Random Forest classification result of unclassified points, in yellow in Figure 6.2

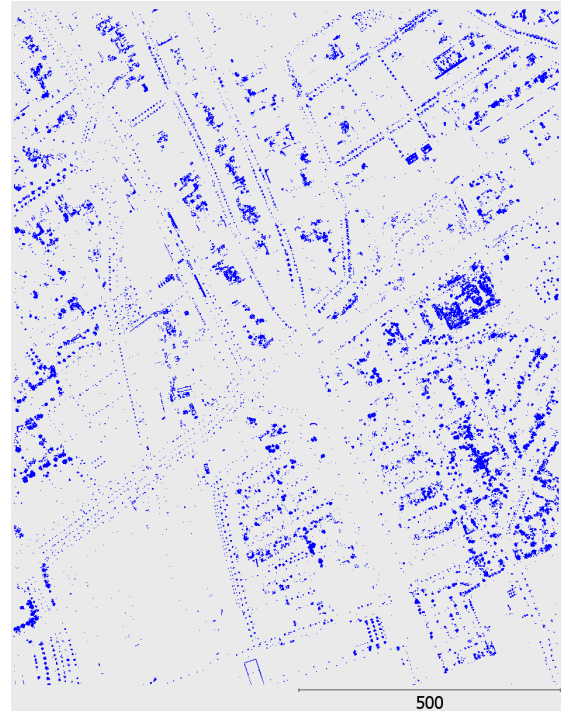
Figure A5: Random Forest classification showing the classification results separated by class of Tile 37EN1_10



(a) Random Forest classification result for classifying trees, in blue in Figure 6.1



(b) Random Forest classification result for classifying non trees, in green in Figure 6.1



(c) Random Forest classification result of unclassified points, in yellow in Figure 6.1

Figure A6: Random Forest classification showing the classification results separated by class of Tile 37EN1_15

A.5 Individual Tree Detection

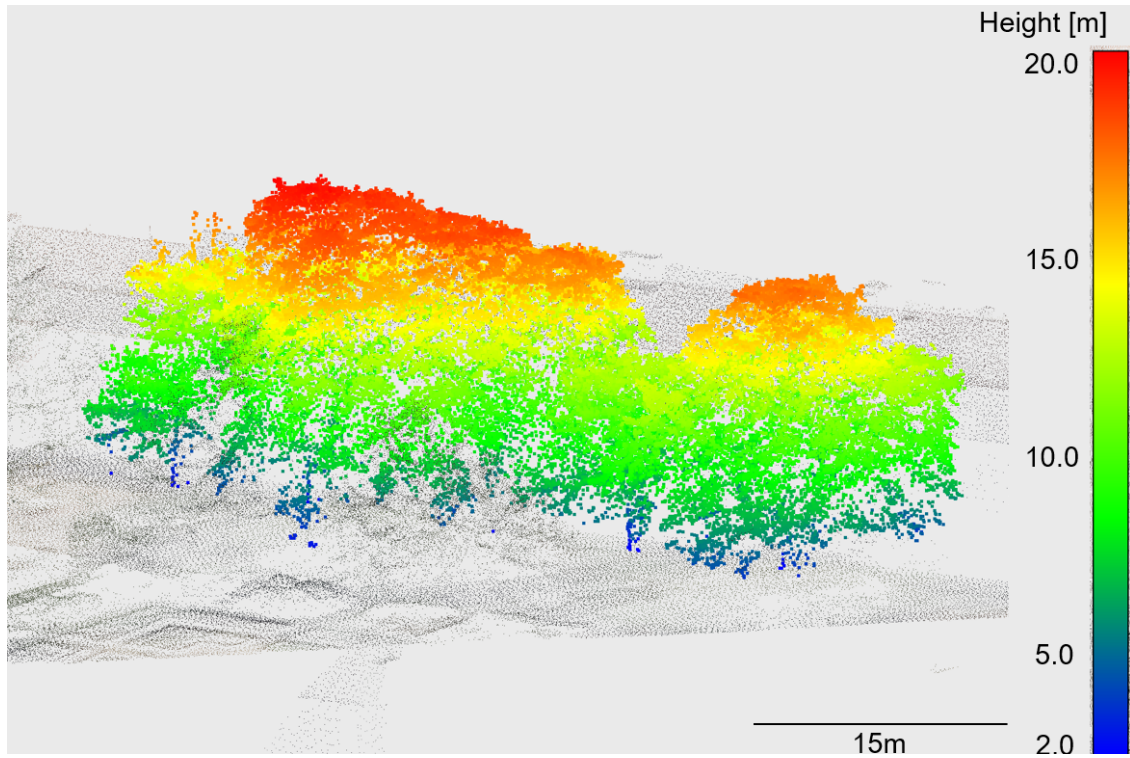


Figure A7: Tree Height side view of undetected Trees in case 3.2 near the Sint Agatha plein in Delft from AHN4, tree points are visualized in CloudCompare with point size 5 and the background point size is set to 1