CZECH UNIVERSITY OF LIFE SCIENCES PRAGUE

Faculty of Environmental Sciences

Department of Spatial Sciences – FES

Automatic Tree Detection and Delineation of Norway Spruce (Picea Abies) using UAV imagery across the Czech Republic

BACHELOR THESIS

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Thesis title

Automatic Tree Detection and Delineation of Norway Spruce (Picea Abies) using UAV imagery across the Czech Republic

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Objectives of thesis

The objectives of this research are (a) to investigate the issue of individual tree detection and delineation (ITCD) of spruce trees using UAV-borne imagery; (b) to implement and apply different ITCD algorithms for selected study area; (c) to evaluate and compare the results of the techniques used and examine them.

Methodology

For this purpose, the processing workflow includes (a) the generation of Digital Surface Models and orthorectified mosaics using UAV-borne imagery; (b) deriving Digital Terrain Models and building Canopy Height Models; (c) applying different ITCD algorithms across the selected study area in Krkonoše Mountains in the Czech Republic; (d) evaluate reached results and critically assess the performance of the algorithms; (e) discuss potential uncertainties and define adequate conclusions.

The proposed extent of the thesis

30-50 pages

Keywords

Forestry, UAV, spruce trees, automatic tree detection and crown delineation

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Recommended information sources

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Author's Statement

I hereby declare that I have independently elaborated the final bachelor thesis with the topic of: '**Automatic Tree Detection and Delineation of Norway Spruce (Picea Abies) using UAV imagery across the Czech Republic'** and that I have cited all the information sources that I used in the thesis and that are also listed at the end of the thesis in the list of used information sources.

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In Prague, March 29, 2023 Salma Bijou

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Abstract

Unmanned aerial vehicles (UAVs) equipped with sensors or LiDAR can be used to collect high-resolution data in forests, which can then be used to generate canopy height models, point clouds, orthomosaics and multiple derived products. This approach is becoming increasingly popular in forest health assessment at the tree level as it provides accurate and detailed information about the crowns delimitation and structure of the forest canopy. To achieve this, different ITCD algorithms were used in the literature. Each algorithm has its advantages and limitations. In this study, I investigated the use of different individual tree detection and delineation (ITCD) of spruce trees using UAV-borne imagery. I tried to implement and apply different ITCD algorithms for our selected study area in Krkonoše Mountains, to evaluate and compare the results of the techniques used and examine them. For this purpose, the processing workflow includes (a) the generation of Digital Surface Models and orthorectified mosaics using UAV-borne imagery; (b) deriving Digital Terrain Models and building Canopy Height Models; (c) applying different ITCD algorithms across the selected study area. The treetop detection and delineation results were first visually validated using reference manually tree crowns. The treetop detection highest precision was achieved using the variable window size local maxima filtering. The highest overall accuracy for the delineation was achieved using the region growing algorithm with F1 score of 98%. The other algorithms, Inverse watershed segmentation, and marker controlled watershed segmentation algorithm demonstrated also impressive accuracy rates in delineating individual trees (with F1 scores of 95.77% and 96.54%, respectively). The findings of this study offer forestry professionals useful insights in determining the most effective method for identifying individual trees.

Keywords: Forestry, UAV, spruce trees, automatic tree detection and crown delineation

Abstrakt

Ke sběru dat s vysokým rozlišením lze v lesích použít bezpilotní letadla (UAV) vybavená pasivními senzory nebo LiDAR skenery. Data lze následně použít k vytváření výškových modelů korun stromů, mračen bodů, ortomozaik a dalších odvozených produktů. Tyto přístupy jsou stále oblíbenější při hodnocení zdravotního stavu lesů na úrovni jednotlivých stromů, protože poskytují přesné a podrobné informace o vymezení korun a struktuře lesního porostu. V literatuře jsou popsány různé algoritmy detekce a vymezení jednotlivých stromů (ITCD). Každý algoritmus má své výhody a omezení. V této studii jsem zkoumala použití různých algoritmů ITCD na příkladu detekce smrků pomocí snímků pořízených bezpilotním letadlem nad vybranou studijní oblastí v Krkonoších. Cílem práce bylo vyhodnocení a porovnání výsledků použitých technik ITCD. Za tímto účelem pracovní postup zahrnuje (a) generování digitálních modelů povrchu a ortorektifikovaných mozaik; (b) odvození digitálních modelů terénu a získání výškových modelů korun; (c) aplikování jednotlivých algoritmů ITCD ve vybrané studijní oblasti. Výsledky detekce a vymezení korun stromů byly vizuálně ověřeny pomocí referenčních ručně vytvořených korun stromů. Nejvyšší přesnosti detekce korun stromů bylo dosaženo při použití filtrování lokálních maxim s proměnlivou velikostí okna. Nejvyšší celkové přesnosti vymezení bylo dosaženo při použití algoritmu Region growing s výsledkem statistiky F1 98 %. Další algoritmy, algoritmus inverzní segmentace vodního díla a algoritmus segmentace vodního díla řízené značkami, rovněž prokázaly působivou míru přesnosti při vymezování jednotlivých stromů (se skóre F1 95,77 %, resp. 96,54 %). Výsledky této studie nabízejí lesnickým odborníkům užitečné poznatky při určování nejefektivnější metody pro identifikaci jednotlivých stromů.

Klíčová slova: lesnictví, UAV, smrky, automatická detekce stromů a vymezení korun

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Abbreviations

UAV: Unmanned Aerial vehicles

ITCD: Individual tree detection and delineation

OBIA: Object Based Image Analysis

CHM: Canopy Height Model

DSM: Digital surface model

DTM: Digital Terrain Model

DEM: Digital Elevation Model

nDSM: Normalized Digital surface model

ITD: Individual Tree Detection

IWS: Inverse Watershed Segmentation

MCWS: Marker Controlled Watershed Segmentation

RG: Region Growing

RS: Remote Sensing

LiDAR: Light Detection and Ranging

NIR: Near Infrared

G: Green channel

KRNAP: Krkonošský národní park

RE: Red Edge channel

Sfm: Structure from motion

GIS: Geographic Information System

RGB: Red, Green, Blue

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1. Introduction

1.1. Research gaps and Problem statement

The forest is an important resource in the Czech Republic and has always been a major concern for public authorities. The imperatives of sustainable development, conservation of resources and international competition are at the origin of the new need management of the natural resources and the environment. From remote sensing images, we can more effectively assess the state of forest resources by using image processing methods to detect changes in forest cover. The delineation of tree crowns is a very important step in determining forest health status and forest management. An ITCD with high accuracy allows a better characterization of crown's spectral signature of spruce trees for the detection of bark beetle attacks. This thesis investigates the problem of tree detection and delineation in UAV images. The high resolution of the UAV images allows us to distinguish individual trees. However, there is a lot of variation in the shape and arrangement of trees, which produces complex images that are difficult to interpret. Our objective is to investigate and compare the results of the different techniques used for the ITCD, and present the most relevant tree top detection and delineation algorithm for our study area. Different ITCD algorithms have been developed in the literature for different purposes, applications and for different tree species, also various techniques have been successfully applied to detect single trees, ITCD has been a well-established area of forestry using different types of remote sensing sources aerial, UAV, and high-resolution satellite imagery. Even though, the delineation is a very important step in the detection of bark beetle attacks of Picea Abies, no study on the effects of different ITCD algorithms applied to UAV imagery was done so far for Norway Spruce specifically. Therefore, it is important to provide information on the accuracy, data processing, and application requirements for single-tree detection using the different available methods. This information can help forest managers choose the most appropriate method for detecting individual trees and take the best decisions regarding the infested trees.

1.2. Research objectives

The objectives of this research are:

- To investigate the problem of individual tree detection and delineation (ITCD) of spruce trees using UAV imagery in Krkonoše Mountains in the Czech Republic.
- To implement different ITCD algorithms for our study area and the proposition of the most relevant algorithm.
- To evaluate and compare the results of the techniques used and examine them.

1.3. Thesis outline

There are four chapters comprising this thesis. The first chapter presents the research problem and gaps, objectives and the structure of the thesis. The second chapter defines the theoretical background , concepts, and various definitions that can serve as an introduction to this field of ITCD such us the different RS sources used for ITCD: aerial photography, multispectral images, satellite airborne images, and UAV images and the history of forestry in Czech Republic. We will also describe different approaches used for the ITCD, and review some studies made from the different of RS sources of data for the purpose of ITCD. Overall, the second chapter will situate the research area, highlight gaps and limitations in the existing research, identify areas where the current study can contribute new insights, and present the problem of tree detection and delineation using drone or UAV images.

The third chapter will describe the design and methodology of the study, including the imagery collection, data analysis procedures, the development for our study area of different tree detection algorithms, and the evaluation/assessment of the results of the used techniques.

Finally, in the fourth chapter, we will interpret the findings of the study, give an outlook and try to identify areas where future research can build on the current study.

2. State of the art (Theoretical background)

2.1. History of Forests in Czech Republic

Forestry has been an important economic and cultural activity in the Czech Republic for centuries. The Czech Republic has a long history of forest management, which can be traced back to the middle Ages. The country's rich history and diverse geography have contributed to the development of a unique forestry culture and management system.

- Early History:

Forestry in the Czech Republic can be traced back to the middle Ages. The first written record of forestry in the country dates back to the 12th century. During this time, forests were managed by local lords who granted forest use rights. However, the use of forests was largely unregulated, and overexploitation was common.

- 18th and 19th Century:

In the 18th century, the Habsburg monarchy began to introduce more modern forestry practices in the Czech lands. The forestry profession was established, and a system of forest inventory and management was put in place. This led to the establishment of forestry schools and research institutions in the country.

- In the 19th century:

The Austrian government passed several forestry laws that aimed to regulate forest use and protect forest resources. These laws established the principles of sustainable forest management, which are still in use today.

- 20th Century:

In the early 20th century, forestry in the Czech lands underwent significant changes due to political and social upheaval. During World War II, the forests were heavily exploited by the occupying Nazi forces, resulting in significant damage to forest ecosystems. After the war, the communist government nationalized the forests and implemented a centralized forest management system. While this system led to some improvements in forest management, it also resulted in significant environmental degradation and biodiversity loss. After the downfall of communism in 1989, the Czech Republic has been transitioning to a more decentralized forest management system. Today, forestry is a major sector of the country's economy, and the country has one of the highest forest coverage in Europe (Simanova 2016, Murray 2006, Report on the Czech Republic 2020).

2.2. Remote sensing in Forestry

Remote sensing technologies have revolutionized the field of forestry, providing valuable information that is essential for effective forest management and conservation. Remote sensing plays a critical role in forestry, providing a cost-effective means of monitoring forest resources and understanding changes in forest ecosystems. Remote sensing technologies, such as aerial photography, satellite imagery, and LiDAR, can be used to gather data on forest cover, biomass, and health, as well as to monitor forest disturbances such as wildfires, insect infestations, and disease outbreaks. Remote sensing images can be used to map forest cover and classify forest types, detect changes in forest health, such as changes in vegetation density or tree canopy cover, which may be indicative of stress or disease. LiDAR technology is very useful to estimate aboveground forest biomass, which is critical for carbon accounting and forest management. Finally, remote sensing images can be used to estimate carbon stocks in forests, providing information on the contribution of forests to the global carbon cycle. (Bill, Ralf. 2018).

2.3. Importance of tree mapping in forestry

Tree mapping or the process of identifying and locating individual trees within a forested area, is an important tool for understanding and managing forest ecosystems. Mapping of trees provides information on the species, size, and location of individual trees within a forest, which is critical for forest management planning. Using that, we can identify areas of high biodiversity, prioritize areas for conservation or restoration, and guide forest management practices such as selective harvesting. It is used to monitor the health of individual trees and detect changes over time, such as changes in tree canopy cover or disease symptoms, to identify areas of the forest that may be at risk of decline or to detect early signs of pest or disease outbreaks (Klouček et al. 2019). Tree mapping is important also for the land use planning as it can be used to inform land use planning decisions, such as identifying areas of the forest that are suitable for development, or areas that should be protected due to their ecological or cultural value (Fisher et al.2017).

2.4. The use of UAVs in forestry

Unmanned Aerial Vehicles (UAVs), commonly referred to as drones, have become an increasingly important tool in forestry for gathering data on forest resources and monitoring forest ecosystems. UAVs can be equipped with cameras, LiDAR sensors, and other instruments to collect data on forest resources, such as tree height, diameter, and density, and to create high-resolution maps of forest cover and composition (Corte et al. 2020). UAVs can also be used to detect insect infestations, such as bark beetle outbreaks, which can cause significant damage to forest ecosystems (Sankey et al. 2017).Using UAVs, we can detect and monitor forest fires, providing real-time information on fire behaviour and helping to guide fire fighting efforts by assessing post-fire damage and plan for restoration efforts. Forest restoration is another area where we can use UAVs; we can use the images to survey areas for potential restoration projects, providing information on the suitability of the site for tree planting, the types of trees that are likely to succeed in the area, and the potential challenges and opportunities for restoration efforts (Mancini et al. 2013). While satellites can provide important data on forest resources and ecosystem health, there are several reasons why UAVs (Unmanned Aerial Vehicles or drones) are often preferred over satellites for forestry applications. UAVs can provide much higher spatial resolution imagery than satellites, which is especially important for forest inventory and mapping. High-resolution imagery from UAVs can provide detailed information on tree size, species, and density, which is difficult to obtain from satellite imagery. UAVs can be flown on demand, providing up-to-date information on forest conditions, while satellite imagery is typically acquired at regular intervals. This can be important for monitoring forest health, detecting changes in vegetation cover and canopy density, and identifying disturbances such as insect infestations and wildfires. UAVs are flexible and can fly at low altitudes, providing more detailed and accurate images of forested areas. This allows for more frequent and targeted monitoring of forest conditions, which can be crucial for early detection of pest infestations, disease outbreaks, or other threats. UAVs are cost effective as the cost of equipment and data processing is often lower than for satellite-based monitoring, UAVs can also be equipped with a variety of sensors, allowing them to collect a wide range of data on forest resources and ecosystem health (Dalponte et al.2015).

2.5. Health status of forest stands

The health status of a forest stand refers to its overall condition and ability to provide ecological services such as carbon sequestration, timber production, wildlife habitat, and recreational opportunities. Several factors can affect the health of a forest stand, including environmental stressors such as drought, insect infestations, disease outbreaks, fire, and human activities such as logging, fragmentation, and land-use changes (McKinley et al. 2011). Foresters and ecologists use a variety of tools and techniques to monitor the health of forest stands such us ground-based measurements of tree growth, mortality, and health indicators such as crown density and foliage color. These methods include also remote sensing technologies such as aerial photography and LiDAR (FAO. 2015). In fact, remote sensing has become an important tool in forest health monitoring, as it allows for large-scale and frequent monitoring and help forest managers identify and respond to these disturbances more quickly, potentially reducing their impact on forest health. For example, changes in forest composition may indicate the presence of invasive species or other disturbances, while changes in forest structure may indicate changes in forest productivity or resilience. We may be able to identify stress factors affecting forest health, such as drought or nutrient deficiencies. By identifying these stress factors, forest managers can take steps to mitigate their impacts and promote forest resilience, to monitor the phenology (i.e., the timing of seasonal events) of forest ecosystems, which can provide insights into forest health and productivity (Ecke et al. 2022, Lausch et al.2017). Assessing the health status of a forest stand involves evaluating its structure, composition, and function. A healthy forest stand typically has a diverse mix of tree species, age classes, and vertical structure. It also has a well-developed understory layer, which supports a variety of plant and animal species. Maintaining the health of forest stands is important for sustaining their ecological functions and services. In the Czech Republic, Salvage cutting has significantly increased over the past three years. In 2019, 32 million cubic meters of raw timber was harvested in the forests. This is really a dramatic increase compared to the previous years. Coniferous wood is the most concerned by 96% (Source: Information on forests in Czech Republic 2021). The majority of harvested wood in 2019 was for Norway spruce infested with Ips Typographus or European spruce bark beetle. This infestation is caused mainly by higher average temperatures and lower precipitation (Bárta et al. 2021). Ips typographus is a species of bark beetle that is native to Europe and parts of Asia. It is one of the most destructive forest pests in Europe, and is responsible for significant damage to coniferous forests in Czech Republic (Hlásny et al.2020). The adult beetles are small (around 5mm in length) and dark brown to black in color. They typically attack weakened or stressed trees, boring into the bark to lay their eggs. The larvae then tunnel beneath the bark, feeding on the phloem and cambium layers of the tree. This feeding activity can disrupt the tree's ability to transport nutrients and water, leading to tree mortality (Hlásny et al.2020).

Forest managers use a variety of methods to monitor and control outbreaks of Ips typographus, including the use of pheromone traps to attract and trap adult beetles, and the removal and destruction of infested trees to prevent the spread of the beetles. In some cases, pesticides may also be used to control populations of the beetles (Fernandez-Carrillo et al.2020).

Figure 1 : European Spruce Bark Beetle (Ips typographus) [Nature Wildlife Photos]

2.6. Spruce Norway (Picea Abies)

Norway spruce (Picea abies) is an evergreen conifer native to Europe. It is one of the most important species of spruce, and it is widely cultivated in North America as well – (Source: Plants for a Future Database). It is an important tree species in the Czech Republic and is widely distributed throughout the country. According to the Report on Forestry in the Czech Republic published in 2021, Norway spruce is the most common and dominant tree species in the country, accounting for approximately 43% of the total forest area. This means this specie is the dominant tree in Czech forests. The spruce is prevalent in the mountainous regions of the country, where it is the main component of the forests (Source: Report on the Czech Republic 2020). Norway spruce trees can grow up to 60-200 feet (18-61 meters) tall, and they have a conical shape with dense, horizontal branches that grow all the way to the ground. The branches of the tree display a spiral pattern arrangement of needles, which are typically 0.5-1 inch (1.3-2.5 cm) long and dark green in color. The spruce trees are known for their dense, fine-grained wood, which is used for a variety of purposes, including construction, paper production, and musical instruments. They are also commonly used as Christmas trees due to their classic conical shape and attractive foliage. In addition to their economic importance, Norway spruce trees provide important ecological benefits. They can help to reduce soil erosion, support wildlife habitats, and sequester carbon dioxide from the atmosphere. However, like many tree species, Norway spruce trees can be susceptible to a range of pests and diseases, and they require careful management to ensure their long-term health and survival (Rabbel et al. 2018).

Figure 2 : Picea Abies (Norway spruce) (Source: Rodríguez Valerón et. 2021)

2.7. Individual tree detection and delineation using Unmanned Aerial Vehicles (UAVs)

One of the primary objectives of individual tree detection using UAVs is to accurately and efficiently estimate forest inventory parameters such as tree species, tree height, tree diameter, and tree volume (Yinghai Ke et 2011). This information is important for forest management and planning, as well as for forest research and monitoring. Another objective of individual tree detection using UAVs is to assess the health of forest stands by identifying and monitoring individual trees that may be affected by pests, diseases, or other stressors. Forest managers and researchers can make use of this data to execute efficient management techniques that ensure the preservation of the forest's health.

- ***ITCD using Satellite Imagery***

There have been several studies that have reported successful individual tree detection and delineation using satellite images. WorldView satellite images are most commonly used for individual tree detection and delineation, there have been a few studies that have reported successful results when using specific approaches like Deep Learning on satellite images. A technique was proposed by Lassalle et al. in 2022 that utilizes a marker-controlled watershed segmentation algorithm in conjunction with a deep learning-based improvement of individual tree crowns. The method was applied to WorldView imagery over four mangrove sites worldwide and achieved accurate detection and area estimation of crowns using either the panchromatic band or a combination of the pan-sharpened visible-near-infrared bands. Braga et al. 2020 used the Mask R-CNN algorithm, a convolutional neural network for tree crown detection and delineation using WorldView very high-resolution satellite images from tropical forests. The results demonstrate promising performance, with Recall, Precision, and F1 score values of 0.81, 0.91, and 0.86, respectively, and a total of 59,062 tree crowns delineated in the study site. In Bengaluru, India, and Gartow, Germany, 30 cm WorldView-3 satellite imagery and 5 cm aerial imagery, respectively, were employed to precisely delineate tree crowns in urban and forested regions using deep learning, and using irregular polygons (not bounding boxes). In both satellite and aerial images, the method achieves an accuracy of 46.3% and 52%, respectively, along with a recall of 63.7% and 66.2%, respectively. (Maximilian et al. 2022)

- ***ITCD using airborne imagery***

Individual tree detection and delineation using airborne imagery is an active research area in remote sensing and computer vision. In a study by Dalponte et al. 2015, four distinct approaches to demarcating trees using airborne laser scanning and hyperspectral data were compared in a forested region of the Italian Alps. The ALS methods had better results than the hyperspectral method in terms of tree detection rate in two out of three cases. The two best-performing methods were based on region growing on an ALS image and clustering of raw ALS point cloud. Pitkänen et al. 2004 investigated three adaptive approaches for individual tree detection on a canopy height model. The CHM was computed from point data acquired with an airborne laser scanner, and the field data consisted of 10 field plots in Kalkkinen, southern Finland. The three methods included smoothing the CHM and identifying local maxima, using crown diameter predicted from tree height to eliminate candidate tree locations based on distance and valley depth, and determining the scale for Laplacian filtering according to the predicted crown diameter. It was found that approximately 40% of all trees and 70% of dominant trees could be detected while maintaining the number of false positives at less than 10%. Hu et al. 2021 examined the performance of three deep learning networks - U-net, Residual U-net, and attention U-net in delineating the Individual Tree Crowns on aerial images. The results showed that U-net had a high accuracy of 0.94 and 0.90 for the two sites, which was significantly better than the traditional machine learning methods.

- ***ITCD using UAV/drone imagery***

Unmanned aerial vehicles (UAVs) have become popular for individual tree detection and delineation due to their high spatial resolution and flexibility in data acquisition. There have been many studies that have reported on tree mapping and extraction using UAV (Unmanned Aerial Vehicle) imagery, using different sensors. Minařík et al. 2020 explored the use of multispectral imagery to automatically delineate crowns using different methods in detecting forest disturbances and tree species. They also examined the impact of point cloud (PPC) density on the accuracy of individual tree crown delineation (ITCD) and feature extraction. The study found that PPC density had a significant impact on ITCD accuracy and that a density of at least 10 points/m2 was necessary for comparable results across different methods. An approach was proposed by Anastasia et al. in 2021, which utilizes automated individual tree crowns delineation to enhance algorithms for species classification and evaluate the vitality of forest stands. Wavelet transformation-based crown segmentation was used for enhancing tree detection. It has been demonstrated that the ITCD algorithm performs well, achieving a crown delineation accuracy of approximately 95%. Jaskierniak et al. 2021 used Unmanned Aircraft Systems UAS LiDAR with a mean point density of 1485 points m−2 in a mixed species eucalypt forests on 39 flight sitesm and developed a novel ITCD algorithm that uses kernel densities to stratify the vegetation profile and differentiate understorey from the rest of the vegetation. This approach generalizes the algorithm across new UAS LiDAR data, resulting in a mean FScore of 0.86.

- ***ITCD for the purpose of Mapping of bark beetle infestations***

Bark beetle infestations can cause significant damage to forested areas and affect the health of individual trees. UAV or drone data can be used to map the extent of bark beetle infestations by detecting and delineating individual trees with infestation symptoms. Some studies that have reported successful individual tree detection and delineation using UAV or drone data for mapping bark beetle infestations. Näsi et al. 2018 used Fabry-Pérot interferometer-based hyperspectral camera on both small unmanned aerial vehicles (UAV) and small Cessna-type aircraft platforms for the comparison, in a city in southern Finland, where the automated identification of mature Norway spruce trees suffering from infestation by the European spruce bark beetle was analyzed. The classification of individual spruces was based on their health status, which was categorized as healthy, infested, or dead. The best results for overall accuracy were obtained using aircraft data, with a 79% accuracy rate However, The employment of a higher resolution UAV dataset resulted in more accurate outcomes, yielding an overall precision of 81%, compared to the aircraft results of 73%. Klouček et al (2019) assessed the potential of inexpensive RGB and modified near-infrared sensors mounted on unmanned aerial vehicles (UAVs) to detect various stages of tree infestation at an individual level. Using an inexpensive UAV-based sensor, it was possible to identify different phases of bark beetle infestation throughout different seasons. These studies demonstrated the potential of using UAV or drone data for mapping bark beetle infestations by using different algorithms for detecting and delineating individual trees along with their infestation symptoms.

2.8. Limitations of drone images for the Individual tree detection and delineation

While drone technology has opened up new possibilities for individual tree detection and delineation, there are still several limitations to be aware of. Here are some potential limitations of drone images for individual tree detection and delineation:

- Limited field of view: Drones have a limited field of view, which means that they may not capture all the trees in an area in a single pass. This can lead to incomplete datasets, and the need for multiple flights to cover the entire study area.
- Low resolution: While drone cameras can capture high-resolution images, the resolution may not be sufficient for detecting and delineating individual trees in densely forested areas or for small trees. This can lead to errors in tree detection and delineation.
- Sun angle and shadow effects: The angle of the sun and shadows cast by trees can affect the quality of drone images. If the sun is low on the horizon or if there are significant shadows cast by the trees, the images may be blurry or incomplete.
- Interference from vegetation: Vegetation can interfere with drone signals and navigation, making it difficult for the drone to fly accurately and capture high-quality images. This can lead to errors in tree detection and delineation.
- Dependence on weather conditions: Drones are sensitive to weather conditions, such as wind, rain, and fog. UnfavourablePr weather conditions can make it hard or impossible to fly the drone, leading to delays or incomplete data collection.

It's important to consider these limitations when using drone images for individual tree detection and delineation and to develop appropriate methods to address them. Combining drone data with other sources, such as LiDAR, may also help to improve the accuracy of tree detection and delineation (Ecke et al. 2022).

2.9. Presentation of different ITCD techniques/algorithms

There are several algorithms that have been used in the literature for individual tree detection and delineation from remote sensing data, including drone images. The most commonly used algorithms are:

- Point cloud-based algorithms: Point cloud-based algorithms use three-dimensional data to identify individual trees based on their height, crown diameter, and other geometric features. They are often used for the detection of individual trees in forested areas (Minařík et al. 2020).
- Object-based image analysis (OBIA): OBIA is an approach that segments the image into objects based on their shape, texture, color, and spatial relationships. It is often used for the detection of individual trees in areas with low to moderate tree density (Jianyu Gu et al.2020).
- Watershed segmentation: This algorithm segments the image based on the topographic features of the landscape, such as ridges, valleys, and peaks. It is often used for the detection of individual trees in areas with complex terrain (Meyer et al.1990).
- Deep learning: Deep learning algorithms use artificial neural networks to identify individual trees based on features learned from large amounts of training data. They are often used for the detection of individual trees in a variety of landscapes, including forested and urban areas (Chen, et al. 2021).
- Template matching: Template matching algorithms search for individual trees based on a pre-defined template of tree shape, color, and texture. They are often used for the detection of individual trees in areas with high tree density (Larsen et al. 2011).

The choice of algorithm depends on the specific research question, the type of remote sensing data available, and the landscape characteristics of the study area. It is very important to select an appropriate algorithm that can accurately detect and delineate individual trees in the target landscape.

3. Methodology and Experimental Design

3.1. Study area: Krkonošský národní park

The study area is located in the Krkonoše National Park in the North Bohemia, a mountain range separates the border between the Czech Republic and Poland (figure(3)). The park was established in 1963 to protect the unique alpine environment and the different flora and fauna of the region. The park covers an area of over 37,000 hectares and includes various types of ecosystems, such as mountain meadows, forests, and peat bogs (Source: Krkonoše National Park website, Natura 2000). Some of the notable species found in the park include the lynx, the Eurasian wolf, the European bison, and the golden eagle. The park is a popular destination for tourists and offers a variety of recreational activities, such as hiking, skiing, and cycling. It also has several educational programs and initiatives aimed at promoting environmental awareness and conservation efforts. In recent years, the park has been facing various environmental challenges, including bark beetle infestations and climate change. The park authorities have been implementing measures to mitigate these impacts and preserve the unique ecosystem of the Krkonoše Mountains. The park is zoned to help manage and protect its natural and cultural resources. It is divided into several zones, each with its own regulations and restrictions. These zones include:

- Core Zone - This zone covers the most sensitive and valuable parts of the park, such as the alpine tundra and areas of high biodiversity. Access to this zone is restricted and only authorized researchers and park staffs are allowed to enter.
- Buffer Zone - This zone surrounds the core zone and includes areas of high ecological and landscape value. Limited tourist activities are allowed in this zone, such as hiking and cross-country skiing.
- Recreational Zone - This zone covers the lower parts of the park and includes most of the tourist facilities and infrastructure, such as ski resorts, hiking trails, and mountain huts. A wider range of recreational activities is allowed in this zone, such as downhill skiing and cycling.
- Landscape Conservation Zone - This zone covers the areas outside of the park's boundaries that are important for maintaining the park's ecological and cultural values. This zone includes areas with traditional land use practices, such as meadows and fields.

The zoning system is designed to balance the protection of the park's natural and cultural resources with the needs and interests of local communities and visitors. The park authorities work to enforce the zoning regulations and ensure that activities within the park are sustainable and compatible with the park's conservation objectives. (Source: Krkonoše National Park website).

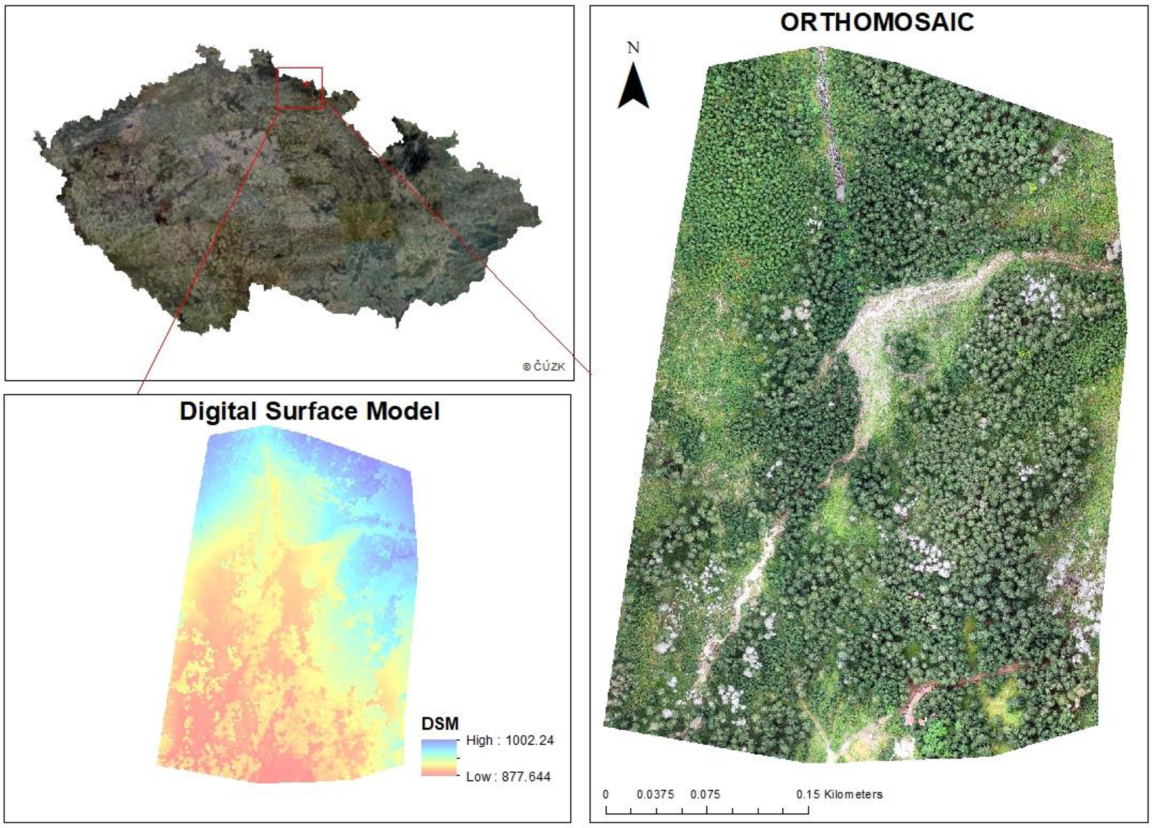


Figure 3 : Location of the Study Area

3.2. Methodology of ITCD

3.2.1. Workflow

The workflow adopted in this thesis is as follows:

- ✓ Image acquisition
- ✓ Pre-processing
- ✓ ITCD implementation
- ✓ Assessment

3.2.2. Image acquisition/Data description

The images used in this thesis were acquired by the Laboratoř GIS a DPZ, Faculty of Environmental sciences, Czech University of Life Sciences. The images acquired are RGB and Multispectral images taken on 20 September 2021, with a Phantom 4 Pro drone (figure (4)) and Phantom 4 Multispectral that provides images in 5 bands table(1). DJI Ground Control software was used for the planning of automatic flight. The flight was conducted at 120 m above ground level with 80% of frontal and side overlaps under the CAVOK (Ceiling and Visibility are OK) conditions. For the purpose of this study, only the RGB images acquired by Phantom 4 Pro and derived photogrammetric products were used for the experiment.

Figure 4 : Image of Phantom 4 Pro

Band Number	Band Name	Centre of the wave wavelength (nm)
1	Blue	450
2	Green	560
3	Red	650
4	Red Edge	730
5	NIR	840

Table 1 : Characteristics of the sensor of Phantom 4 Multispectral

3.2.3. Pre-processing

Pre-processing of UAV imagery involves a series of steps to prepare the images for analysis and interpretation. Metashape image-matching software was used for image processing. The steps involved in pre-processing of the UAV imagery are:

- Image calibration and georeferencing: Sfm and image calibration involves correcting distortions in the images caused by lens imperfections, sensor errors, or atmospheric conditions. This step is crucial to ensure accurate measurements and analysis. Georeferencing involves aligning the UAV images with a geographic coordinate system. This step is necessary to accurately locate features on the ground and to overlay the UAV data with other spatial data sources.
- Generation of Digital Surface Model and Digital Terrain Model: This method involves using UAV imagery to create a 3D model of the terrain. The images

are taken from multiple angles, and the software uses algorithms to calculate the elevation and shape of the terrain. The DTM can be generated using the same steps after ground filtering.

- Generation of normalized DSM: The process of generating a nDSM involves creating a digital surface model (DSM) of the terrain, which includes the height of all objects on the ground surface. Next, a digital terrain model (DTM) is generated to represent the bare earth surface without any vegetation or other objects. The nDSM is then calculated by subtracting the DTM from the DSM, leaving only the height of vegetation and other objects above the ground. (Figure 6).

Pre-processing of UAV imagery is a critical step in generating high-quality data for next analysis.

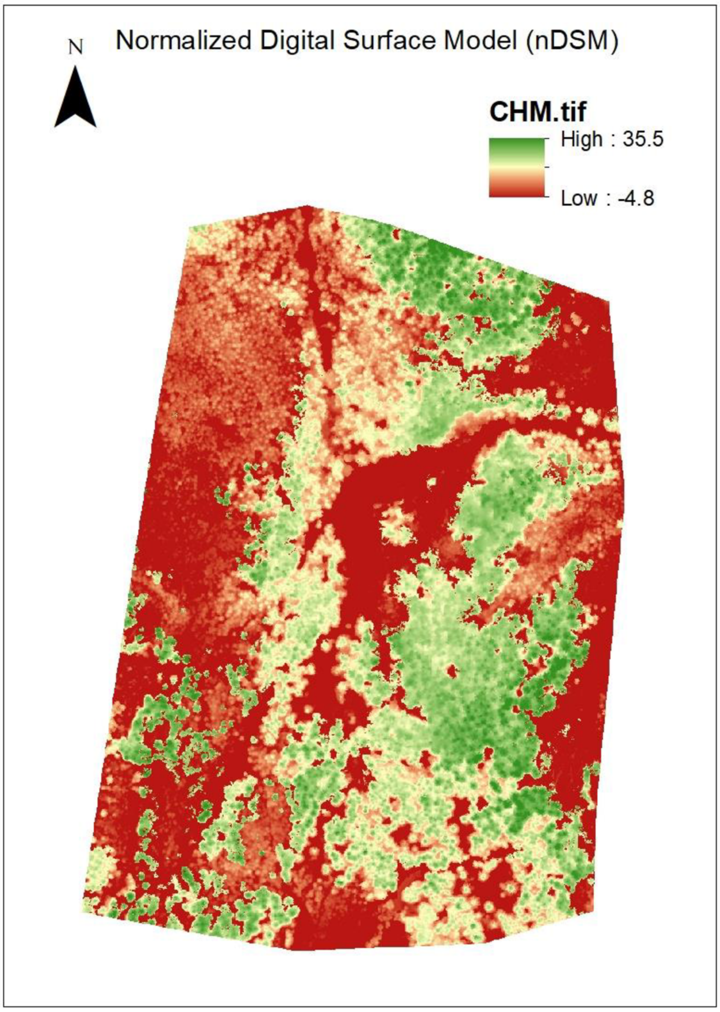


Figure 5 : Normalized Digital Surface Model of the study area

3.2.4. ITCD Implementation

3.2.4.1. Local Maxima Filtering

Local maxima filtering is a technique commonly used in image processing and computer vision to detect and delineate individual objects, including trees. The basic idea of local maxima filtering is to locate the maximum pixel values in an image or a specific region of interest, which represent the center of individual objects or features (Monnet et al. 2010). In the context of individual tree detection, local maxima filtering are often applied to digital elevation models or Canopy height models derived from remote sensing data such as LiDAR or drone-based photogrammetry. The DEM represents the height of the terrain surface and can be used to identify individual tree crowns that are above the surrounding canopy. The local maxima filtering process involves identifying peaks in the CHM that meet certain criteria, such as a minimum height or area threshold, and applying a filter to remove false positives. The filter can be designed to exclude peaks that are too close to each other or too elongated, which may represent noise or other non-tree features. Once the local maxima are identified and filtered, the remaining peaks are considered to represent individual tree crowns. Additional processing steps, such as crown delineation, can be applied to extract the crown size and shape information (Monnet et al. 2010). A local maximum filtering is a widely used approach for individual tree detection and delineation and has been shown to be effective in a variety of landscapes and data types. However, it is important to carefully select the filter parameters and thresholds to ensure accurate results and to validate the outputs with ground truth data when possible.

Algorithm: The algorithm was implemented using Model Builder in ArcGIS Version 10.8.1 (Esri. (2021). The model builder is presented in (Appendix VI.)

a. Input : nDSM
b. Get the forest mask with trees higher than 16 m
c. Filter and smooth the image with a low pass filter
d. Get the maximum of the nDSM using a 2 m circular window
e. Vectorize the output
f. Output : Treetops shapefile
g. Create buffer around the treetops: Trees crowns.

The result of the method is presented in (Appendix I.)

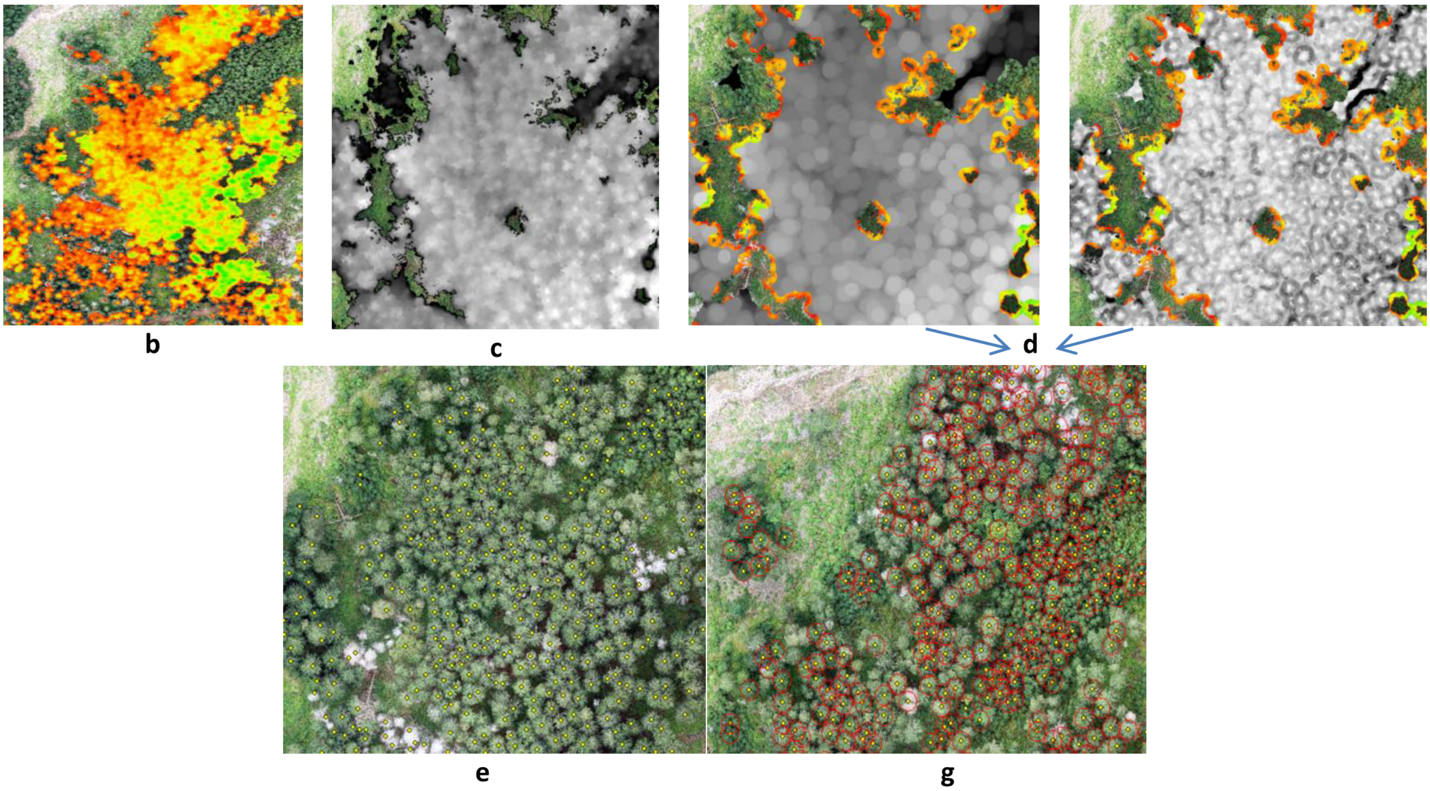


Figure 6 : Local maxima filtering workflow (steps b, c, d, e and g)

3.2.4.2. Inverse watershed segmentation

Inverse watershed segmentation is a technique used in image processing to separate different objects or regions of an image. In the context of individual tree detection and delineation, inverse watershed segmentation can be used to separate trees from their surroundings and identify their boundaries. The steps are:

Apply inverse watershed segmentation to the image. This will create regions of the image that correspond to individual trees, by considering the image as a topographic surface and flooding it with water from the highest points (the trees) until the water meets at the lowest points (the boundaries between trees).

Once the trees have been identified using the inverse watershed segmentation, post-processing steps can be applied to refine the boundaries and remove any false positives or false negatives. Finally, the output of the inverse watershed segmentation can be used to extract quantitative information about the trees, such as their size and shape, or to create health maps or other visualizations of the tree distribution.

Inverse watershed segmentation is a powerful tool for individual tree detection and delineation, and can be applied to a wide range of image data, including aerial photographs, satellite images, and LiDAR data. However, it does require careful parameter selection and post-processing to achieve accurate results (Nasiri et al. 2021).

Algorithm: The algorithm was implemented in ArcGIS Version 10.8.1 (Esri. (2021).

a. Input: nDSM.
b. Inverse the nDSM: trees canopy is transformed into watersheds, where treetops become ponds and tree crowns become watersheds.
c. Smooth the nDSM.
d. Compute the Flow direction: to create drainage basins. The flow direction calculates the direction water flows, using slope from trees crown to ponds (trees tops).
e. Compute the Basin: create a raster delineating drainage basins by identifying edge lines between basins.
f. Vectorize the basins.

The result of the method is presented in (Appendix II.)

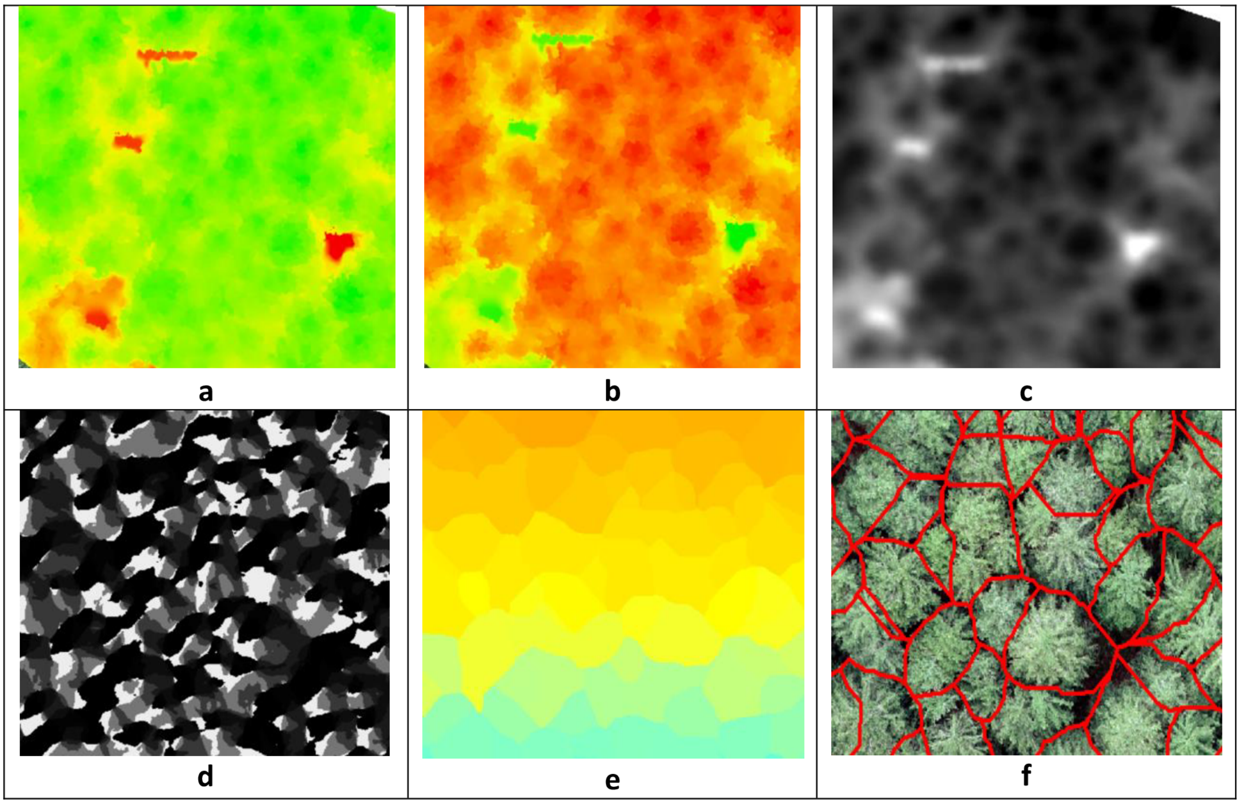


Figure 7 : Inverse watershed segmentation workflow (steps a, b, c , d, e and f)

3.2.4.3. Marker controlled watershed segmentation

Marker controlled watershed segmentation can be a useful technique for individual tree crown delineation (ITCD) using drone imagery. After identifying potential tree crown locations using a tree detection algorithm or manual annotation. We use these identified tree crown locations as markers for the marker-controlled watershed segmentation. This will create regions of the image corresponding to individual tree crowns (Meyer et al.1990).

The approach utilizes a canopy height model and the watershed function to segment the crowns. The detected point positions of the treetops serve as a guide for segmentation.

Algorithm: the algorithm was implemented in R (R Core Team. (2021).)

a. Input : nDSM or CHM
b. Detect treetops using vwf function in R.
c. Delineate crowns using mcws function in R.
d. Vectorize the crowns. (Appendix III.)

The result of the method is presented in (Appendix III.)

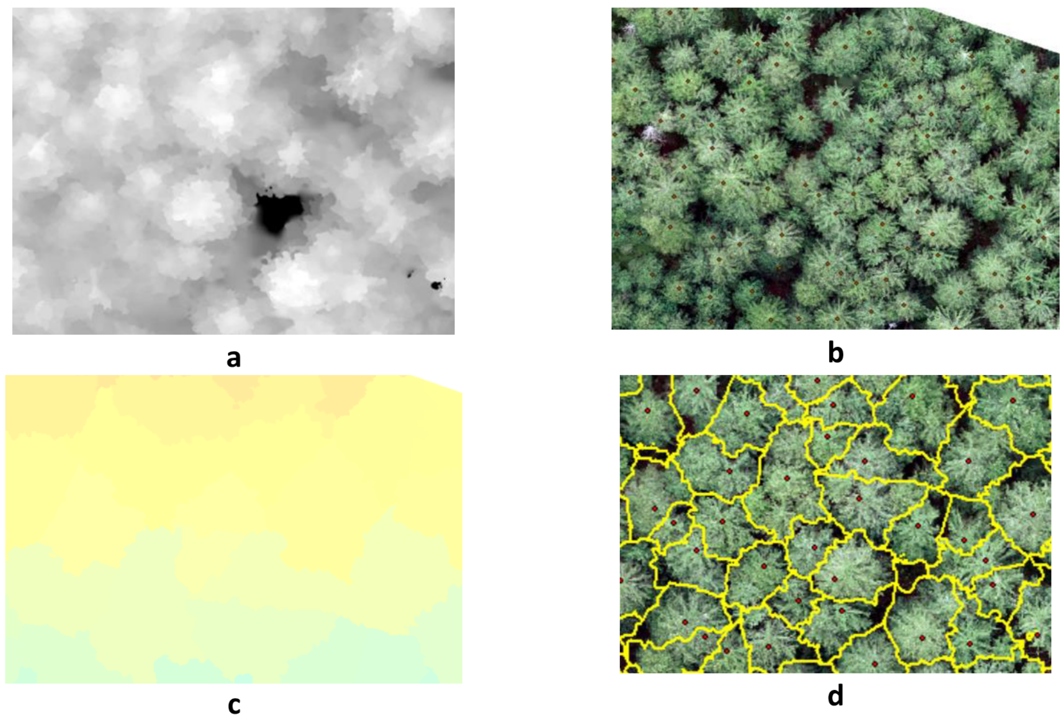


Figure 8 : Marker controlled watershed segmentation workflow (steps a, b, c , and d)

3.2.4.4. Thiessen Polygons

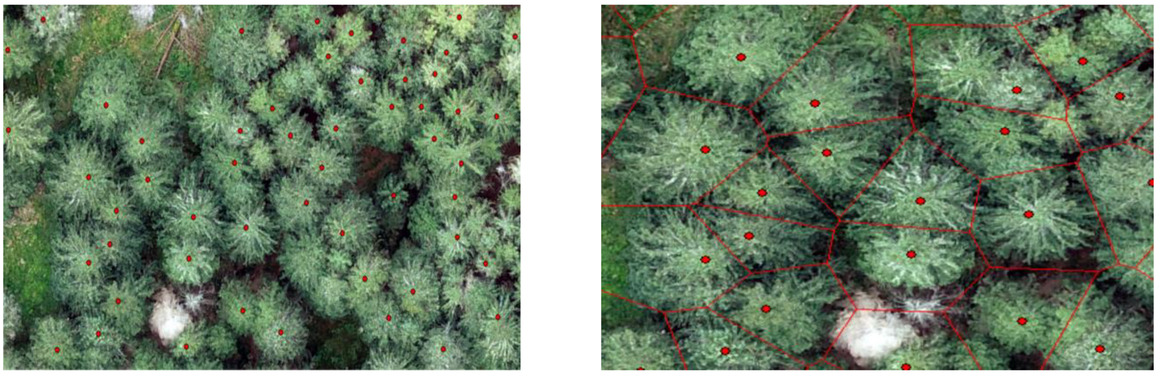
Thiessen polygons, also known as Voronoi diagrams, can be used for individual tree detection and delineation by dividing an area into non-overlapping polygons based on the proximity of data points (individual tree crowns) (ArcGIS Resources. Create Thiessen Polygons (Analysis))

.

Algorithm: was implemented in ArcGIS Version 10.8.1 (Esri. (2021).

a. Input: Potential tree top locations (treetops)
b. Generate Thiessen polygons for each tree crown location. Thiessen polygons represent the area of the image that is closest to each tree crown location.

The result of the method is presented in (Appendix IV.)



a b

Figure 9 : Thiessen polygons workflow

3.2.4.5. Region growing segmentation

Region growing is a technique used in image processing to segment an image into regions or objects based on similarity criteria. It involves selecting a seed pixel or region and iteratively adding neighboring pixels or regions that meet specific similarity criteria. First, we choose a seed pixel or region of interest.. we define a similarity criterion, such as intensity, texture, or color, that will be used to determine whether neighboring pixels or regions should be included in the segmented region. Find the neighboring pixels or regions that meet the similarity criterion and add them to the segmented region. Repeat step 3 until no more neighboring pixels or regions can be added (Novotný et al. 2011).

In forestry applications, region growing can be used to segment individual tree crowns from aerial or satellite imagery, where the similarity criterion could be based on color, texture, or shape. However, it may be challenging to accurately define the similarity criterion for different tree species or in complex forest environments with overlapping tree crowns. Therefore, careful parameter selection and post-processing are required to achieve accurate and reliable results.

Algorithm: was implemented in SAGA GIS (2.3.2) (Conrad et al.2015).

a. Input: Treetops shapefile generated automatically in the previous steps and RGB orthomosaic.
b. Rasterize the treetops shapefile.
c. Resampling of the grids for the 2 input images.
d. Apply the seeded region growing using the user-defined threshold.
e. Save the generated segments in TIF format.
f. Vectorize the segments >> delineated trees.

The result of the method is presented in (Appendix V.)

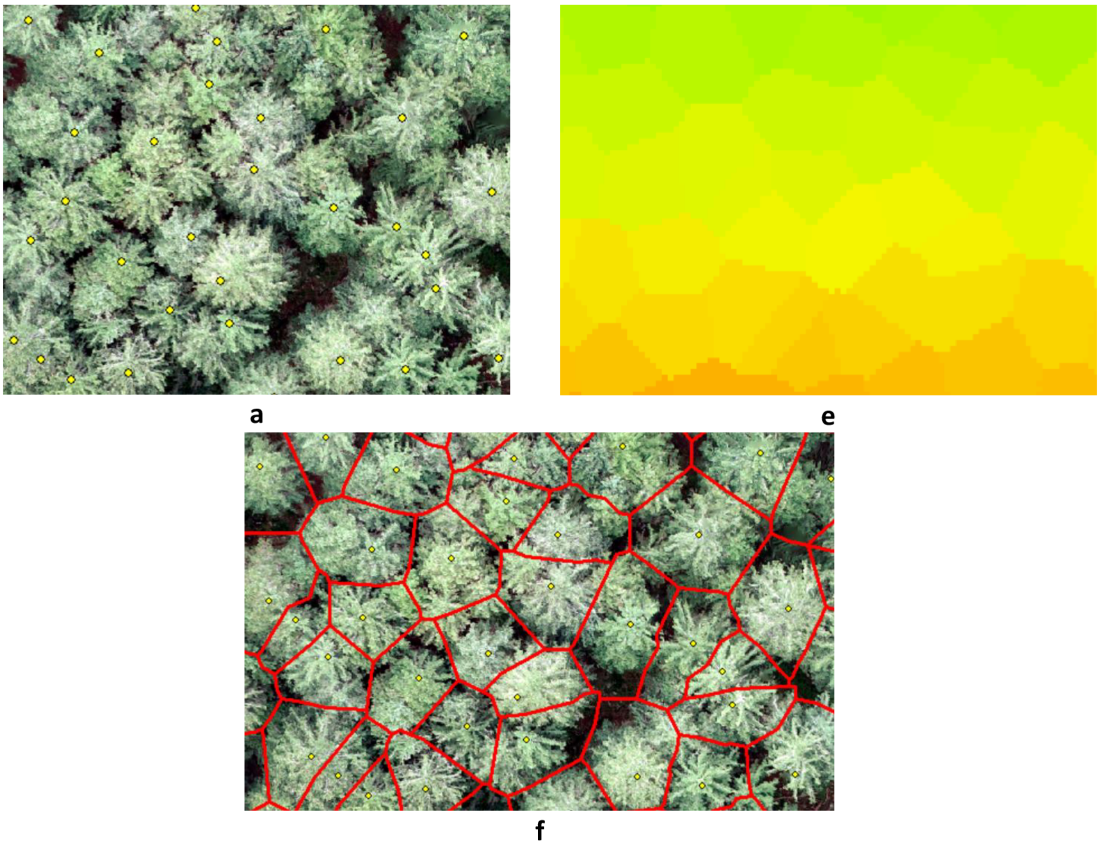


Figure 10 : Region growing workflow (steps a, e and f)

3.2.5. Accuracy assessment

The accuracy assessment of crown delineation in this study was based on how well each segmented crown matched with the ground reference delineation. The reference crowns were manually digitized using ArcGIS. The model's performance was evaluated using three metrics: recall, precision, and F1 score. Recall measures the proportion of trees correctly identified by the model out of all the trees identified through an independent visual assessment. Precision represents the proportion of correctly identified trees out of all the trees predicted by the algorithm. The F1 score provides a single metric summarizing the model's overall performance, taking into account both recall and precision. Recall is a metric used to evaluate the effectiveness of a binary classification model in correctly identifying positive cases, and its formula is:

Recall = True Positives / (True Positives + False Negatives)

where True Positives represent the number of cases correctly identified as positive, and False Negatives are the number of cases that were actually positive but were incorrectly classified as negative by the model. Precision is defined as the ratio of True Positives to the total number of actual positive cases, and its formula is:

Precision = True Positives / (True Positives + False Positives)

True Positives are cases accurately identified as positive, while False Positives represent the number of cases predicted as positive by the model but were actually negative. The F1 score is a harmonic mean of precision and recall and is calculated using the following formula:

F1 score = 2 * (precision * recall) / (precision + recall).

In the context of the study, True Positives refers to the quantity of pixels that were correctly classified as trees, while False Positives represents the number of pixels wrongly identified as trees. Lastly, False Negatives corresponds to the number of pixels that actually depicted trees but were not detected by the algorithm.

4. Results

Two approaches were included to assess the accuracy of the procedures 1) The location of treetops and their number, and 2) Evaluation the quality of the tree crown delineation.

4.1. Evaluation of Treetop detection

The adaptive algorithm was tested for individual tree detection on the CHM. The window is adjusted to fit the size of each individual tree. Based on our visual interpretation, we can clearly notice in figure (12) the difference in treetop detection between the 2 methods (fixed and variable). The small trees with relatively different crown size was successfully detected using an adaptive window size. The fixed window method ignored the large number of suppressed, small trees that were not detected from the CHM. An example of tree locations produced from the two CHM filtering methods on our study area is presented in figure (12). From the table (2), we can see that the number of treetops identified using the 2 different approaches vary from one to another with higher number of treetops using the adaptive approach (341 trees).

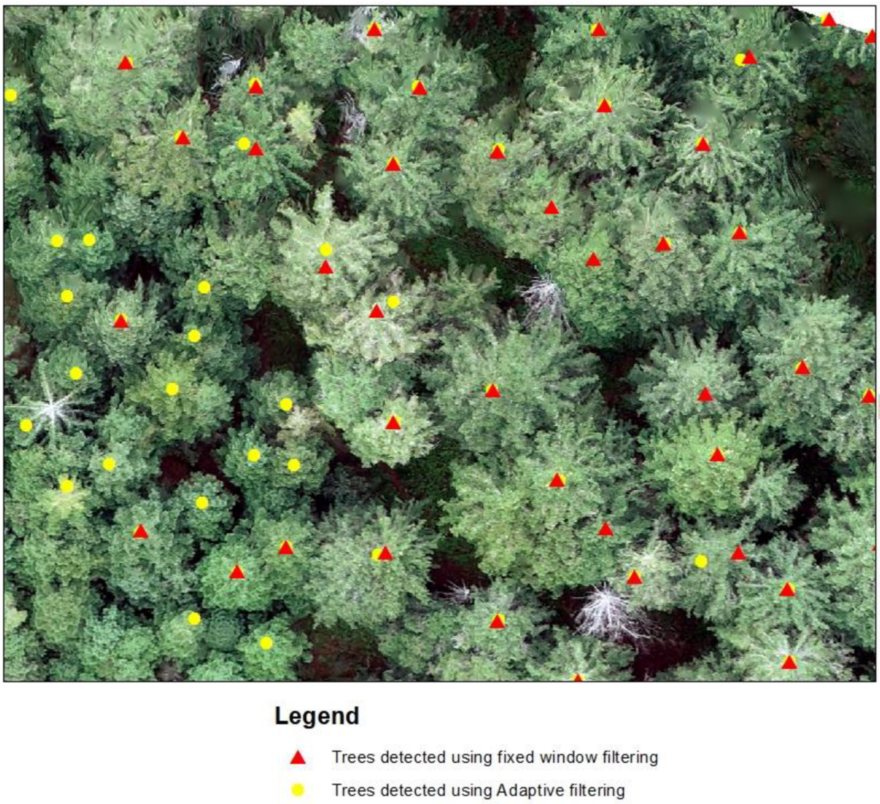


Figure 11 : Tree Top locations produced by Adaptive and fixed window method

Local Maxima Adaptive	Local Maxima Fixed
341	273

Table 2 : Comparison of local maxima filtering methods

4.2. Evaluation of ITCD delineations

4.2.1. Manual delineation of reference data

The RGB imagery was used to manually delineate reference tree crowns. The manual delineation is based on the expert visual assessment. We were able to delineate a total of 266 reference crowns for our study area to be used for accuracy assessments in ArcGIS 10.8.1 as seen in figure (13).

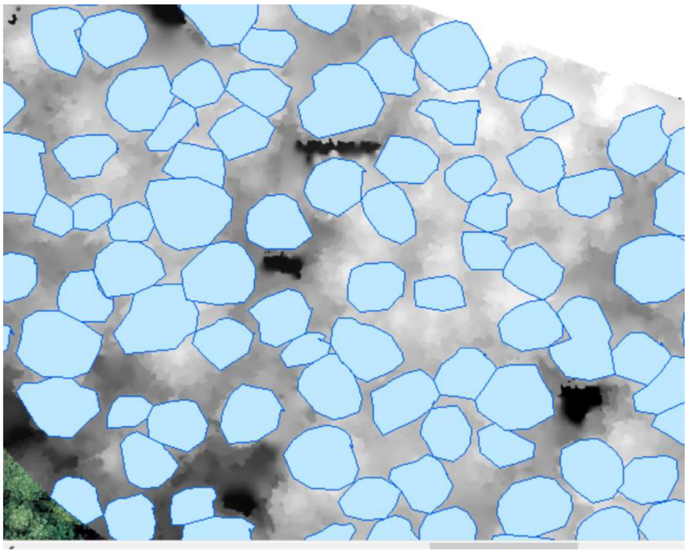


Figure 12 : Manually delineated reference tree crowns

The manually delineated reference crowns were used for the analysis to assess the results of each delineation result based on a visual assessment of the overlap between the limits of each crown.

4.2.2. Accuracy of algorithms for spruce tree detection and delineation and Comparison

The table (3) compares the number of crown counts resulting from each delineation algorithm with the reference crown counts in our study area.

Reference crowns count	Delineated crowns count				
	Local maxima filtering	Inverse watershed segmentation	Marker controlled watershed segmentation	Seeded Region growing	Thiessen polygons
266	341	343	351	339	339

Table 3 : Count of manually and automated delineated trees

The table (4) demonstrates the accuracies of different ITD algorithms. The accuracy assessment of the individual tree crown delineation was performed using recall, precision and F1 score. The highest overall accuracy was found using the seeded region growing algorithm. The lowest overall accuracy was found using the inverse watershed segmentation. See figure (14).

Algorithms	Recall	Precision	F1 score
Inverse watershed segmentation	0.956395	0.959184	0.957787
Marker controlled watershed segmentation	0.976676	0.954416	0.965418
Seeded Region growing	0.976608	0.985251	0.98091

Table 4 : Accuracy assessment of automated delineated trees

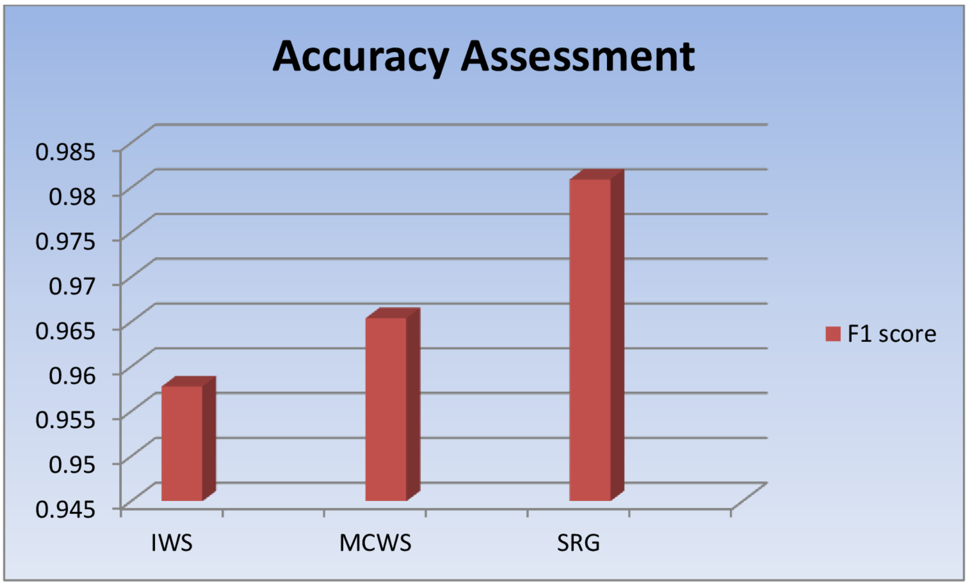


Figure 13 : Accuracy assessment of the ITCD algorithms

5. Discussion and outlook

The objective of this study was to assess different approaches for the automated methods of ITCD in our study site in Krkonošský National Park, Czech Republic. Using high spatial resolution UAV imagery and a derived CHM, inverse watershed algorithm, marker controlled watershed segmentation, Thiessen polygons and seeded region growing algorithms were visually compared with reference manually delimited crowns and evaluated using accuracy assessment metrics.

The manual delineation of reference trees was not based on ground truth data neither on an expert forester to delimit the crowns on the image. This explains the differences in the number of trees count between the automated methods and the manual delineation. The manual delineation has an important impact on the assessment of the different ITCD, as the visual assessment for our study area resulted in lower number of reference trees than what was detected by the algorithms. However, if manual delineation is chosen as the method, it is important to have input from experts who are knowledgeable about the specific species and environmental conditions being studied. They can help ensure that the delineation accurately reflects the characteristics of the trees in the area and can identify any potential errors or biases in the delineation process. Expert opinion can be used to establish guidelines and protocols for manual delineation to ensure consistency and accuracy across different observers, to help reduce variability in the results and increase the reliability of the data.

The treetop detection was also assessed using a fixed and adaptive window size. In the context of tree detection, the choice between using an adaptive or fixed window size depends on the specific requirements of the task and the characteristics of the imagery being analyzed. A fixed window size approach is simple and has lower computational process; it involves using a predetermined size for the window for the filtering. This approach is useful and effective when the size of the trees is of similar size and shape and relatively consistent and uniform across the entire forest dataset. If the area is wider. This method results in lower accuracy detection. A window that is too small may miss larger trees, while a window that is too large may identify multiple smaller trees as a single large tree (Larsen et al. 2011). While the adaptive window size can lead to improved accuracy in detecting trees, as the window can be adjusted to fit the size of each individual tree. The accuracy of tree detection is affected by the density of forest as small trees in overlapping trees can be neglected by the algorithm. In 2021, a semi-automated refined approach was introduced by Shiyue Chen et al. 2021 for detecting individual trees in overlapping canopy mountain forests using RGB imagery acquired from unmanned aerial vehicles. The authors proposed an adaptive local-maximum algorithm that includes a series of steps to improve the detection of trees in the challenging mountain forest environment and the results showed that the proposed algorithm outperformed the other algorithms (object-oriented feature segmentation and multiscale segmentation technique), achieving higher accuracy in individual tree detection with a an accuracy of more than 80% in dense forest.

The results of the different ITCD algorithms are different. For our study area, the seeded region growing algorithm had the higher F1 score of 98% in comparison with other algorithms. This may be due to the differences in the input used by the algorithms: CHM, treetop points, RGB orthomosaic. The use of different kind of inputs to implement the algorithm can affect the accuracy of delineation. The overall accuracy for our study area was achieved by the seeded region growing algorithm. It confirms the results of the authors who investigated ITCD algorithms using UAV-based high-resolution imagery in a broadleaf Hyrcanian forest, where the region growing algorithm generated the most appropriate and accurate results (Miraki et al. 2021). The study assessed also the impact of various forest structures, filtering, and diverse tree species on the precision of the tree delineation algorithms, as the authors were able to identify different results after setting specific values and parameters for the different algorithms (best delineation with region growing found for a spatial resolution of 100 m). The region growing has shown its effectiveness in the delineation process of trees. Dalponte et al (2015) investigated 4 approaches for delineation on ALS and hyperspectral data. The most favourable outcomes were obtained with a technique that utilized region growing on an ALS image. Some authors tried to refine the results of the method. Jianyu Gu et al. (2020) proposed method involves a combination of region growing and growth space considerations, by using region growing to segment individual tree crowns from UAS imagery and then consider growth space to refine the delineation of tree crowns. The study's findings indicated that the method can be very useful particularly in areas with complex terrain and overlapping tree crowns. The outcomes indicated that the least precise method was IWS, which is consistent with earlier research findings (Miraki et al. 2021, Dalponte et al. 2015).

There were several advantages and inconvenients for the use of each type of algorithm. The buffer method is sufficient for the delineation in monocultures. But, it is not appropriate in a mixed forest due to the limited and simplified crown delineation (Klouček et al. 2019). The major limitations to inverse watershed segmentation that affected its effectiveness in our scenario, was the over-segmentation. It is one of the main limitations of inverse watershed algorithm. In cases where the image has a lot of noise or the boundaries between objects are not well-defined, the algorithm may produce too many small regions that do not correspond to meaningful objects. Another step of cleaning the segments or resetting the parameters of the algorithm is needed to keep only the segments that correspond to the real trees. As for the effectiveness of marker controlled watershed segmentation. This method was so sensitive to the choice of parameters. The parameters need to be such as the threshold needs to be carefully tuned to obtain good results, which can be time-consuming and require expert knowledge.

The problematic of ITCD is still an issue. While ITCD algorithms tend to perform well in coniferous forests, their efficacy in mixed forests remains a challenge. As a result, there is a growing demand for ITCD in regions where mixed forest stands dominate. The extent to which automated individual tree crown detection (ITCD) methods can be applied in various forest types, as well as the factors that impact the effectiveness of these techniques, remains uncertain. Automated delineation is very important because it is one of the most important steps in forest health assessment and management.

Further studies need to be investigated using different spatial resolutions for large areas and in different type of forests to accurately assess the results of the different ITCD algorithms used in this study. It is clear that more research is still for the ITCD and segmentation techniques and also the methods for accuracy assessment.

6. Conclusion and contribution of the thesis

Individual tree detection and delineation using UAV (Unmanned Aerial Vehicle) technology has revolutionized the way we collect data for forestry management. By using high-resolution images captured by UAVs, we can accurately and efficiently identify and locate individual trees within a forest area. This technology has numerous advantages over traditional field surveys, including reduced time and cost, increased accuracy, and the ability to cover a large area in a short amount of time. The process of individual tree detection and delineation using UAV involves capturing high-resolution images of the forest area, processing these images to identify individual trees using computer algorithms, and delineating the boundaries of each tree. The resulting data can be used for a precise mapping of forest disturbance and bark beetles attacks in infested areas. We have performed first trial of investigation of multiple ITCD approaches in the Krkonoše National park in Czech Republic. Overall, the Marker Controlled Watershed Segmentation, Region Growing, and Inverse Watershed Segmentation algorithms provided slightly different results, but the RG produced higher accuracy compared to the other algorithms. In the context of the fast improvement of the tools for forest health assessment at the local or regional scale using different RS techniques and especially UAVs, it becomes very clear that the project presented in this thesis is expandable and suggests avenues for further research. The most interesting possible future work could be the use of multispectral UAV imagery or other source of data. The aim would be to use an approach which does not rely on structural data such us CHM derived from UAV imagery or LiDAR. LiDAR data require additional time for capturing and processing additional dataset and the CHM derived from UAV imagery is not always accurate especially in dense forested areas. The objective should be to find the best method to be applied only on optical images. Another possible limitation which opens up new areas for exploration is the use of approaches that are independent on the shape or size of the crowns, in any type of forest (dense or non-dense forests, coniferous or broadleaved), and in different lighting conditions. The use of UAV technology for individual tree detection and delineation is a promising development tool. It has the potential to improve our understanding of forest disturbances and facilitate better decision-making for sustainable forest management practices.

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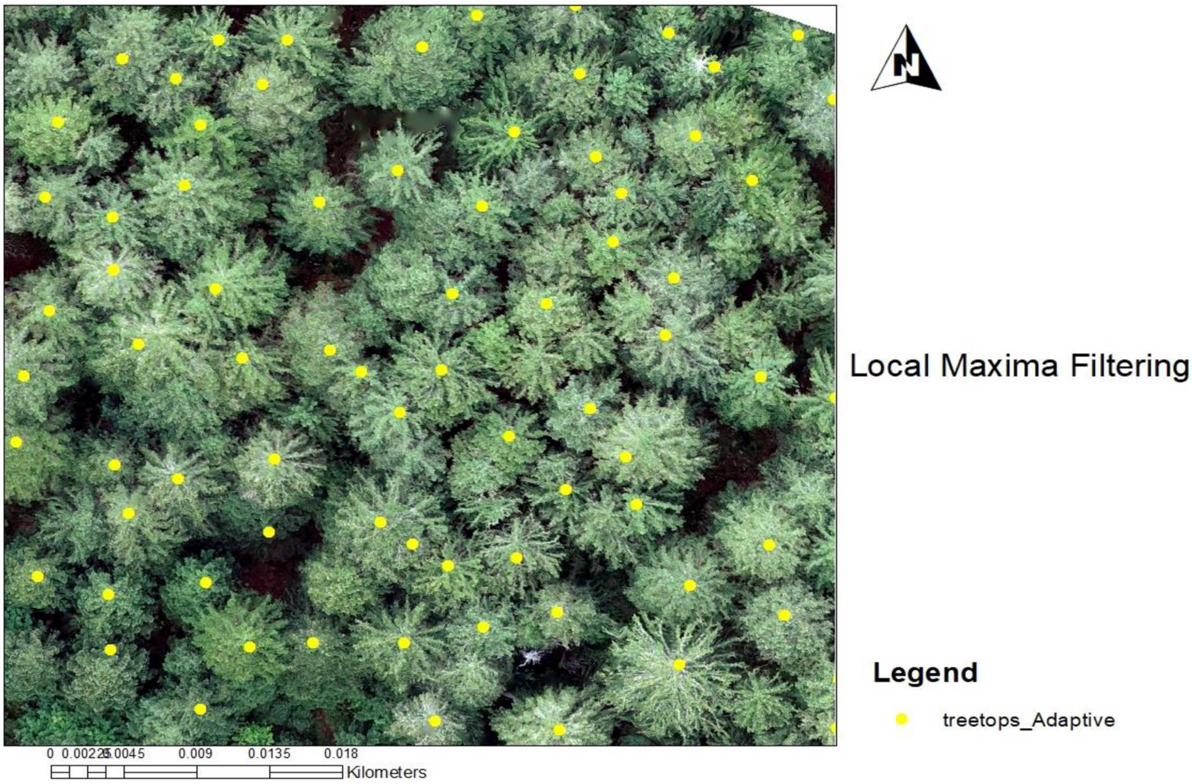
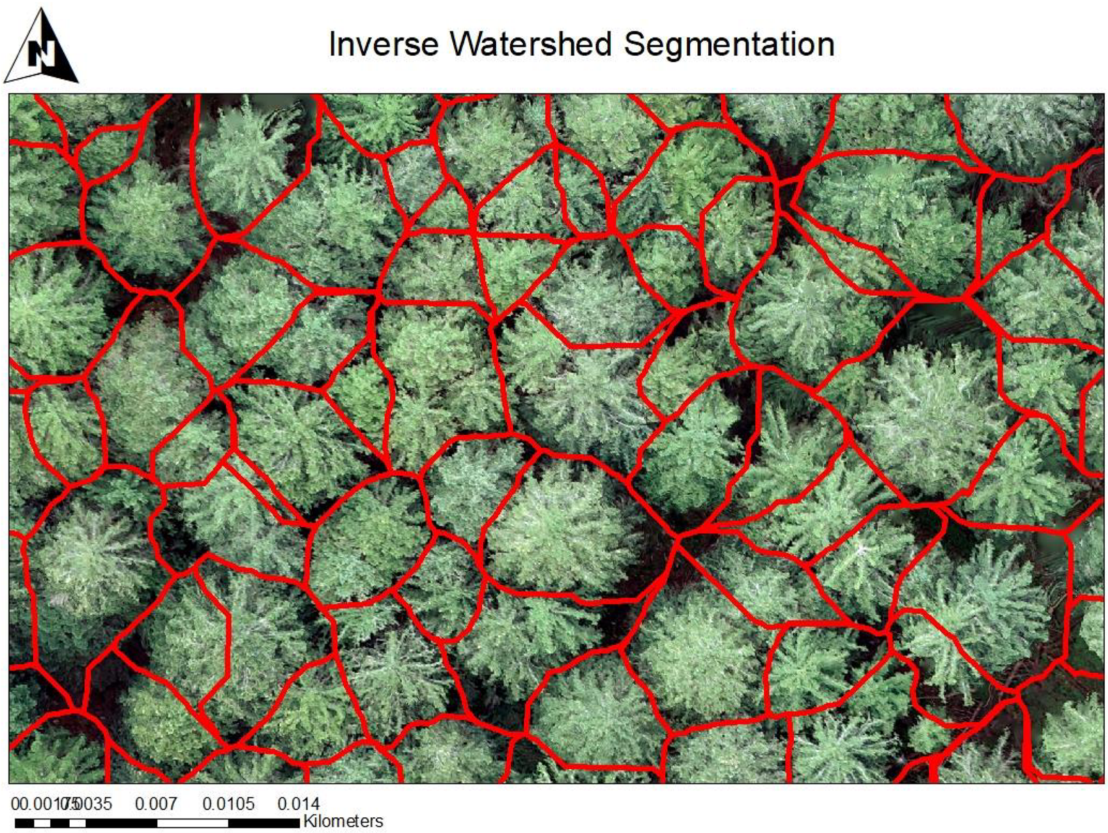
8. Appendices

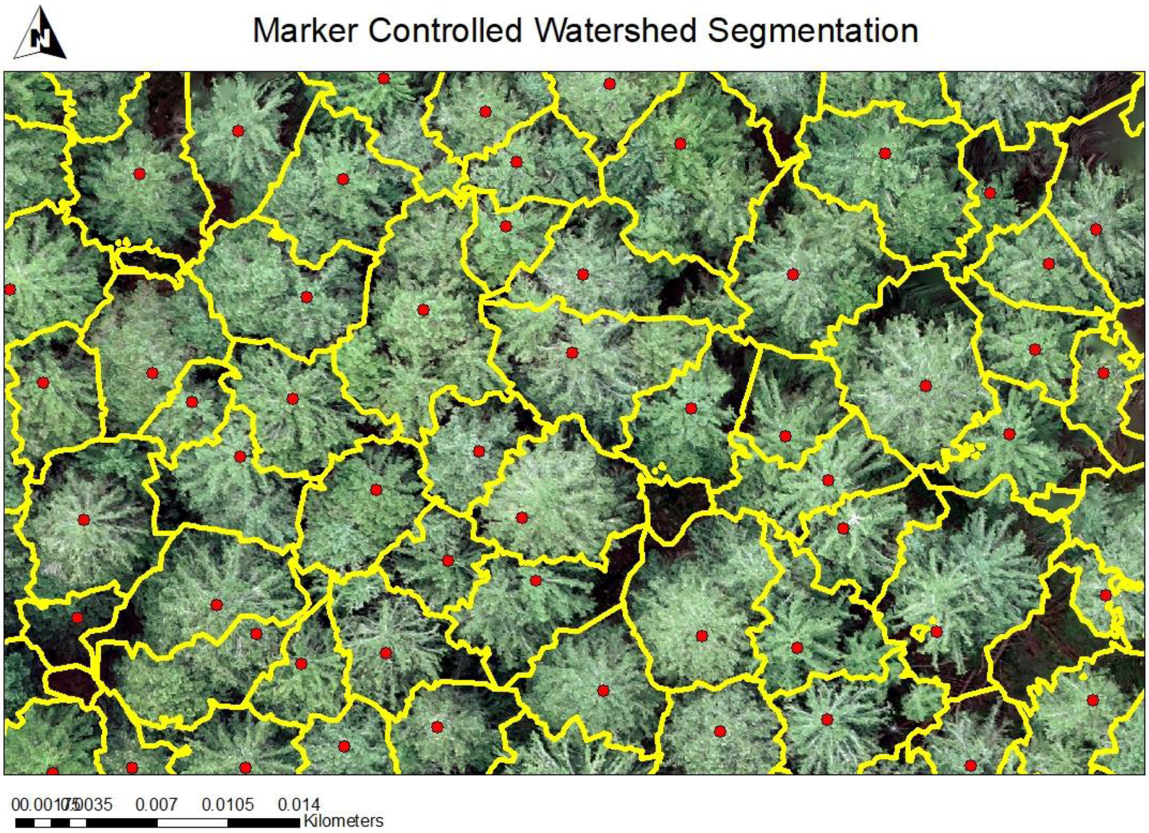
Appendix I.



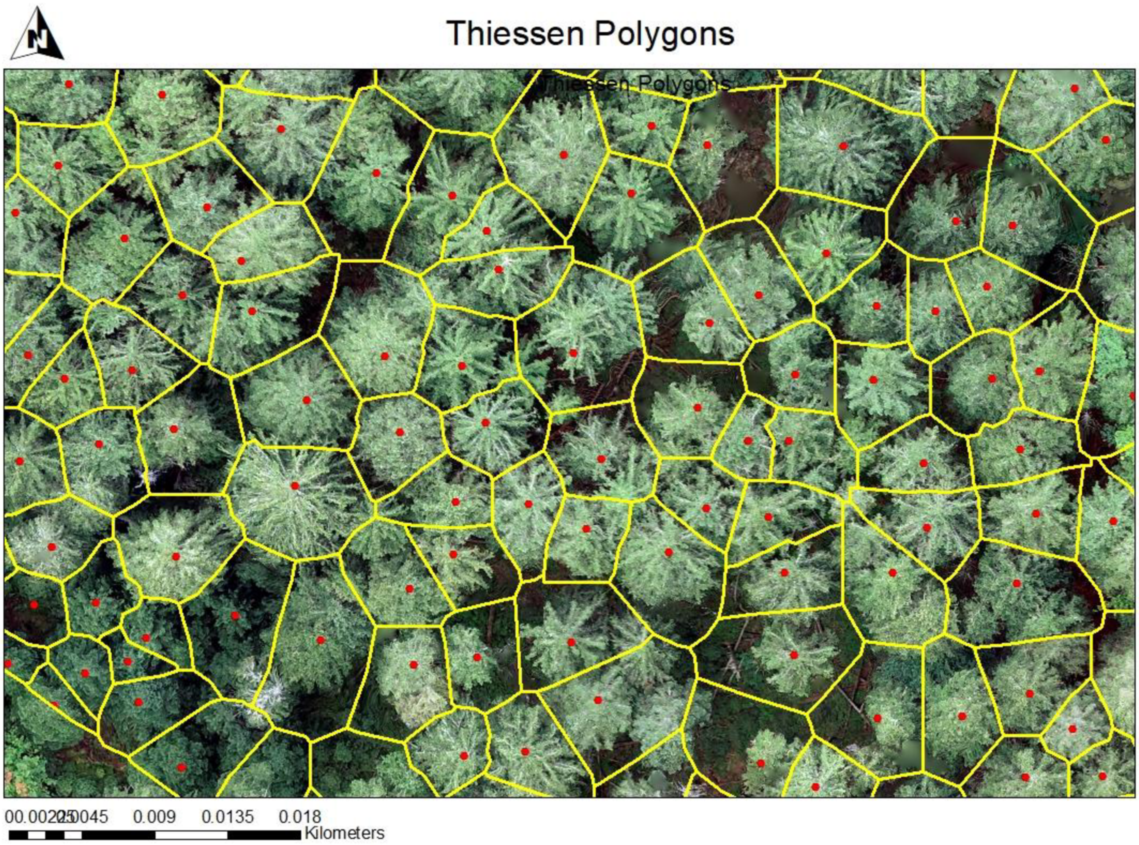
Appendix II.



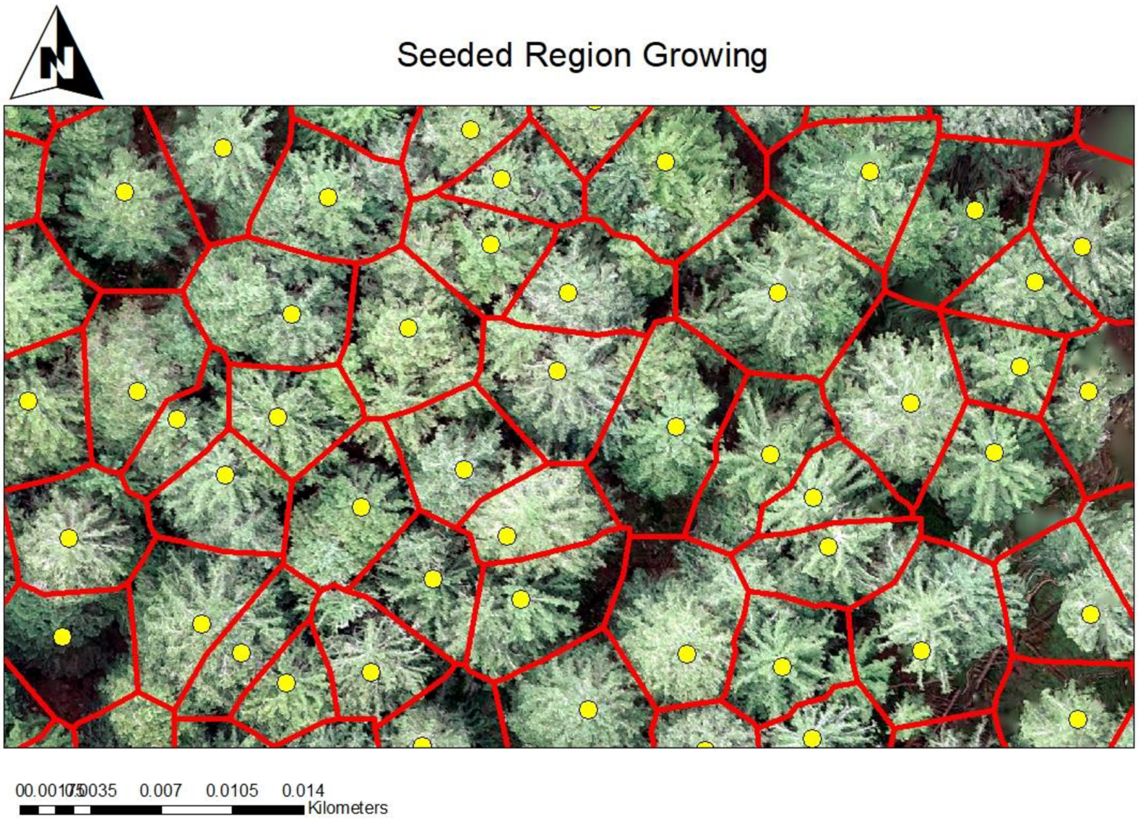
Appendix III.



Appendix IV.



Appendix V.



Appendix VI. Model Builder for Local Maxima Filtering