

Does the implementation of Automatic Individual Tree Crown Delineation (ITCD) impact the early detection of bark beetle (BB) infestation in Norway spruce forests?

Salma Bijou¹, Lucie Kupková¹, Lucie Červená¹, Jakub Lysák¹

¹ Department of Applied Geoinformatics and Cartography, Faculty of Science, Charles University, Albertov 6, Prague 2, Czech Republic - (salma.bijou, lucie.kupkova, lucie.cervena, jakub.lysak)@natur.cuni.cz

Keywords: UAV, Norway spruce, crown delineation, bark beetle, ITCD, green and yellow stage.

Abstract

Early detection of bark beetle (BB) infestations in Norway spruce forests is essential for effective forest management. While UAV imagery offers high-resolution data, selecting appropriate crown pixels to detect subtle spectral changes during early BB infestation stages is still a challenge that needs further investigation. This study examines the impact of automatic Individual Tree Crown Delineation (ITCD) methods in detecting early-stage BB infestations, particularly during the green-to-yellow stage. On July 19, 2022, high-resolution multispectral UAV imagery (2 cm) was acquired using the DJI Phantom 4 Multispectral sensor over a 4-hectare forest plot in Krkonoše National Park, Czech Republic. Treetop detection was performed using local maxima filtering, while four ITCD algorithms: Buffer, Marker-Controlled Watershed Segmentation, Thiessen polygons, and seeded region growing, were used for crown delineation. Spectral data from five bands and five vegetation indices were extracted for each automatic ITCD method, as well as for manually delineated crowns, across 11 infested and 11 healthy trees. Spectral separability was assessed using the Mann-Whitney test. The findings revealed that the 3-meter fixed window filter effectively detected treetops but encountered challenges with double detections and missing smaller trees. Seeded region growing proved the most accurate for crown delineation. Statistical analysis showed that red-edge and near-infrared spectral bands, along with vegetation indices (NDVI, GNDVI, OSAVI, and RENDVI), successfully separated healthy from infested trees using both automatic ITCD and manual delineation. However, manually delineated crowns exhibited greater sensitivity to spectral variations, especially in the red band, making manual delineation more effective for early-stage BB detection. While automatic ITCD methods excelled in detecting Excess Green Index (ExG) differences. Though, automatic ITCD methods are computationally efficient, manual delineation or refinement of automatic ITCD is needed for accurate monitoring of subtle spectral changes during BB infestations (green-to-yellow transition). Precise crown delineation and early BB detection rely on high-quality pre-processing, expert knowledge (of infestation stages by foresters), and field observations (e.g., tree positioning using GPS or total station and BB symptoms), with multitemporal imagery aiding in tracking infestation progression within the tree crowns.

1. Introduction

Individual Tree Crown Delineation (ITCD) is key to precision forestry as it provides foresters and researchers with detailed tree-level data essential for efficient forest management (Qiu et al., 2020). Before analyzing remote sensing data in forest environments, ITCD is usually performed. This two-step process generally involves detecting treetops, by identifying the position of an individual tree (its center) and grouping pixels of each tree crown into distinct objects, by outlining the contour and shape of the tree crown (Zhen et al., 2016, Zheng et al., 2023).

Detecting and delineating trees is important for mapping species diversity, detecting tree diseases, and quantifying biomass and carbon storage to support climate change mitigation efforts (Shah et al., 2011, Sun et al., 2019, Barnes et al., 2017). Given the significance of ITCD, remote sensing imagery, including satellite and aerial images, along with structural data like Canopy Height Models (CHMs), has emerged as an efficient alternative to the labour-intensive traditional field methods. Both classical and deep learning approaches have been applied to detect and delineate forest canopies, offering significant improvements in accuracy and efficiency. Examples of classical ITCD methods include local maximum filtering,

template matching, object-based image analysis for tree detection and region growing, valley following, for tree delineation (Zheng et al., 2023). High-resolution satellite images, such as WorldView-3 and 2, have enabled improved accuracy in crown delineation (e.g. mangrove stands, tropical forests.) through conventional and deep learning methods (Lassalle et al., 2022; Braga et al., 2020; Freudenberg et al., 2022). Airborne imagery has also been widely studied. For instance, in a study conducted by Dalponte et al., 2015, they demonstrated that ALS (Airborne Laser Scanning) methods outperformed hyperspectral data for tree detection in the Italian Alps, with region growing and clustering emerging as the most effective techniques. Hu et al., 2021 demonstrated that U-net deep learning models achieved superior accuracy (0.94 and 0.90) for crown delineation on aerial images. Novotný et al., 2011 used local maxima and seeded region growing techniques, achieving detection accuracy of up to 84% and delineation accuracy of 64%.

Unmanned Aerial Vehicles (UAVs) are increasingly favoured for individual tree detection and delineation because of their very high spatial resolution and versatile data collection capabilities at the crown level, used in forest inventory studies (Zheng et al., 2023). To accelerate processing, and eliminate the need for lengthy manual detection and delineation of trees, studies have focused on automatic ITCD algorithms using UAV images in diverse

forest environments (Miraki et al., 2021). These methods aim to estimate key forest parameters on the tree level, such as tree species, count, and height (Yin et al., 2016, Diez et al., 2020, Safonova et al. 2021, Panagiotidis et al., 2017), and to monitor forest health by detecting trees affected by bark beetles (BB) or other pests (Minařík et al., 2020, Tao et al., 2020, Honkavaara et al., 2020).

For forest health assessment, UAV images, coupled with advanced image analysis techniques, have proven to be valuable tools in the detection and monitoring of Norway Spruce trees attacked by European Spruce bark beetles (*Ips typographus*), which significantly damage spruce forests (Bijou et al., 2023). This insect attacks trees through multiple stages based on crown discoloration (Green stage, yellow stage, red stage, and grey stage; Niemann et al., 2005). The high spatial resolution of UAV images can help in the early detection of BB-infested trees on the crown level during the green attack stage (when no symptoms of infestation are visible), to prevent the spread to neighboring trees and the escalation into an epidemic.

Although ITCD techniques using UAV images for forest health assessment are relatively simple in coniferous forests (monocultures of Norway spruce), monitoring crown health differs from estimating tree parameters, as it focuses on analyzing spectral information within crown pixels. During BB infestation, there is a gradual decline and death of spruce trees, often starting from the outer branches and progressing inward. This progression is reflected in the spectral information within crown pixels. The effectiveness of ITCD is then influenced by the various stages of BB infestation, particularly the transition between the green and yellow stage, which exhibits invisible, uneven, or minor crown discoloration. Therefore, accurate ITCD in high-resolution UAV images requires selecting smaller pixels relative to the crown size and carefully choosing pixels (infested) within tree crowns to detect subtle spectral changes indicative of BB attacks within this particular early stage.

This research is important and novel because, to our knowledge, no studies have specifically assessed the impact of various automatic ITCD algorithms on the assessment of BB-infested trees, particularly considering the infestation stage. Although Minařík et al., 2020, explored different algorithms for crown delineation using multispectral UAV imagery in a mixed urban forest, their work did not focus on the impact of ITCD on the early detection of infestations in spruce monocultures. Their findings indicated that automated ITCD methods, coupled with high-density photogrammetric point clouds, could effectively replace manual delineation for bark beetle detection and tree sanitation, yet the challenge of the impact of ITCD on the 'early' infestation detection remains unexamined. Therefore, it is crucial to understand how these algorithms affect BB infestation detection, especially in the period of transition from green to yellow attack stages. This insight can help remote sensing experts appreciate the significance of ITCD and choose the most effective method for detecting and delineating individual trees at this stage, ensuring accurate crown pixel capture and excluding irrelevant ones. The study aims to evaluate

how different automatic methods for detecting and delineating spruce trees influence the accuracy of BB attack assessment during the green-to-yellow infestation stage using UAV-captured multispectral imagery. The primary research question investigates whether incorporating various crown pixels, identified through manual delineation or automated methods, improves or compromises the assessment of tree vigor and health in trees at the early stages of BB infestation. Additionally, the study seeks to identify which spectral bands and vegetation indices are affected by different automatic crown delineation algorithms.

2. Methods

The experiment was conducted in a forest plot within the Krkonoše Mountains National Park (KRNAP), in the Czech Republic, dominated by Norway spruce (*Picea Abies*). A 4-hectare area in Dolní Dvůr was selected for its new BB activity in 2022 (Figure.1). RGB and multispectral images (2 cm resolution) were captured using a Phantom 4 Multispectral RTK drone on July 19, 2022, at 56.9 m altitude with 80% image overlap. The drone provides images in 5 single bands: blue, green, red, red-edge, and near-infrared (NIR). The spruce trees included in the study were first identified (by foresters) as infested at the beginning of the summer season (June 3rd). They were subsequently captured on July 19th, during the mid-to-late stages of bark beetle infestation, which coincided with noticeable changes in crown discoloration. This date was selected as it marks the transition from the green to yellow infestation stage, with some trees showing yellowing needles while most remained green. The location of infested trees is depicted in Figure 1. (e). The entire analysis workflow is illustrated in Figure 2.

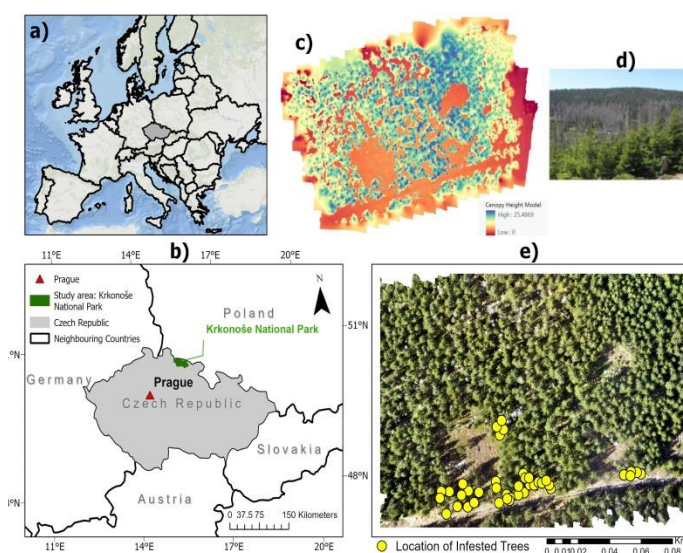


Figure 1. Study site: a) Inset location of the Czech Republic, b) Location of the study area in the Krkonoše National Park, c) Canopy height model, d) Picture of the park landscape, e) RGB UAV Orthomosaic of the study area and the location of bark beetle-infested trees.

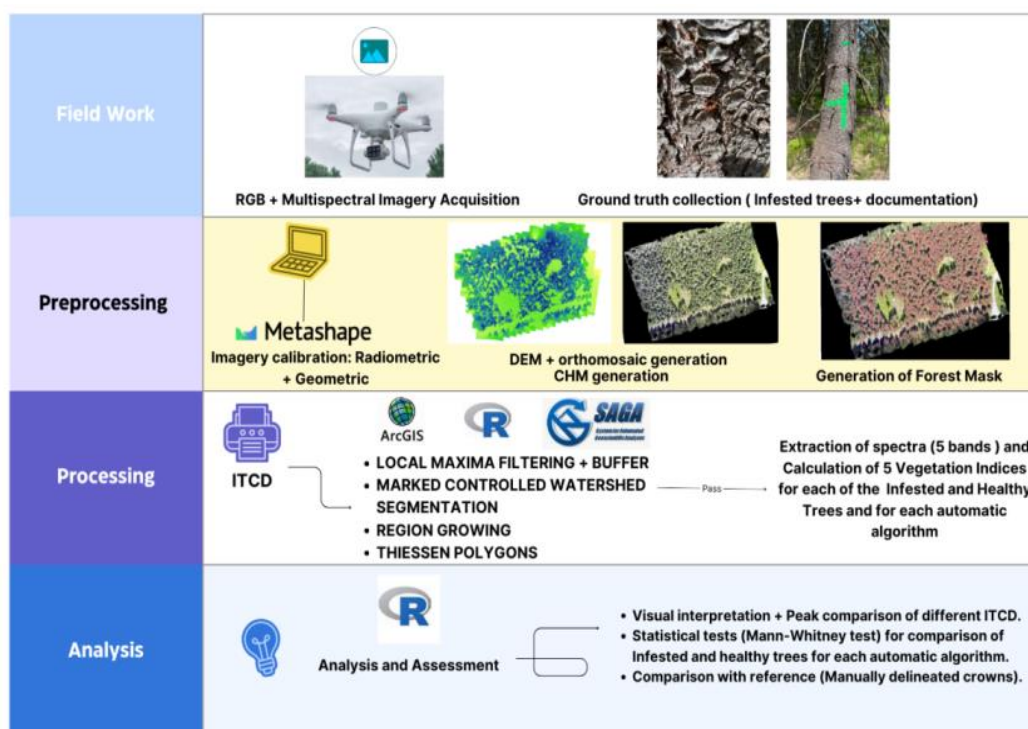


Figure 2. Workflow of the study

2.1 Data pre-processing

The RGB and multispectral images were pre-processed in Agisoft Metashape Professional v1.7.2 software (www.agisoft.com, Agisoft LLC, St. Petersburg, Russia), including image alignment and mosaicking, generation of Digital Elevation Model (DEM), and orthomosaics (Bijou et al., 2023). The multispectral (MS) orthomosaic was radiometrically corrected using flat field correction, performed in ENVI v5.5 software, using flat carpet that was placed in the field before the flight. In order to generate a canopy height model (CHM), the resolution of a lidar-captured digital terrain model (DTM) was adjusted through resampling to match the resolution of the digital elevation model (DEM). Then, the CHM is calculated by subtracting the DTM from the DEM, leaving only the height of vegetation above the ground. To remove the understory and non-forest objects from the orthomosaics, a series of three masks were created. The first mask involved applying a thresholding technique to the CHM in order to extract an elevation mask, which effectively removed the ground. The second mask was generated by calculating the Excess Green Index and then performing an unsupervised classification (ISO Cluster) with the objective of distinguishing between forest pixels and shrub pixels, to generate 8 classes. Only three classes were selected for further analysis. The third mask was designed to eliminate tree shadows by using the NIR band with a threshold value of more than 0.3. By combining these three masks, a Boolean mask raster was generated, accurately identifying and isolating pixels of Norway spruce trees. This Boolean mask was subsequently used to mask both the MS orthomosaic and the CHM, excluding any undesired

elements from the analysis. Figure 3. (a) illustrates the final tree (s) mask.

2.2 ITCD implementation

After successfully isolating the spruce trees from the rest of the objects (in the CHM and the MS orthomosaic), we conducted the step-by-step process for detecting and delineating individual trees using the different proposed algorithms, described in detail in the following subsections.

2.2.1. Generation of spruce treetops and buffering

For the detection of treetops within the forest plot, we used in our study the local maxima filtering technique. This method examines each pixel and its neighboring pixels to identify a local maximum. By comparing pixel values, the filter determines the highest value as the local maximum. The pixel with the maximum value from this process corresponds to the treetop's location (Mohammed, Bouzkraoui, 1999). Figure 3. illustrates the workflow adopted for treetop detection using the local maxima filtering approach. The algorithm was implemented using Model Builder in ArcGIS Version 10.8.1 (Esri. (2021)). To achieve this, we applied a fixed circular window on the CHM to filter and smooth the image using a low-pass filter, in order to reduce the number of local maxima wrongly detected. Next, we applied focal statistics to obtain the maximum value within a 3-meter fixed circular window. Subsequently, the identification of potential treetops was carried out by subtracting the smoothed image from the local maximum image. We then vectorized the output to generate a treetops shapefile. Finally, we created a 2-meter buffer around the treetops to delineate the tree crowns, which corresponds to the first automatic ITCD method adopted in our study (Figure3).

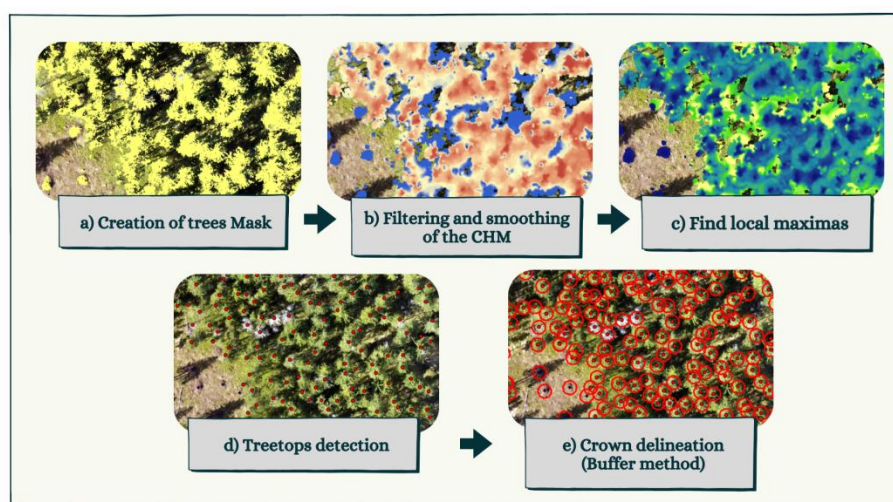


Figure 3. Process of generation of treetops and buffering, a) The final trees mask, b) CHM filtered and smoothed, c) Identification of local maxima, d) Treetops detected (red dots), e) Buffer method used for crown delineation (red circles).

2.2.2. Crown delineation using automatic ITCD algorithms

The generated treetops in the previous step were used to apply the different automatic ITCD algorithms. Table 1 summarizes the different type of input data used for the processing of each automatic ITCD method.

Algorithm	Input data
Buffer	CHM + treetops
MCWS	CHM + treetops
RG	Orthomosaic + treetops
Thiessen polygons	Treetops

Table 1. Input dataset for each automatic ITCD algorithm. MCWS: Marker Controlled Watershed Segmentation, RG: Region Growing.

2.2.2.1. Marker Controlled Watershed Segmentation

We used Marker controlled watershed segmentation (MCWS) algorithm in our study to partition the MS orthomosaic into distinct regions. The method operates by treating the image (CHM) as a topographic surface, where the intensity values represent the elevation of the surface. The algorithm starts by identifying markers or seed points within the image that correspond to the treetops. These markers can be manually specified or automatically determined using a fixed or adaptive window filters. Next, the algorithm simulates the flooding of the topographic surface (CHM) starting from the markers. It progressively fills the basins, represented by the regions surrounding the markers, until the basins merge at the watershed lines. The watershed lines correspond to the boundaries between different tree crowns (Meyer et al., 1990). The markers used correspond to the treetops generated using a fixed window filter in the previous step (Section 2.2.1). The delineation was done using 'mcws function' available in R taking into account the linear function ($F = x \times 0.08 + 0.5$, x is the height of the tree). The generated edges or watershed lines are then converted to polygon in Shapefile format. The segmentation is guided by markers/treetops, resulting in more accurate and controlled segmentation, to prevent over-segmentation.

The algorithm was implemented in R (R Core Team, 2021) using ForestTools and lidR packages.

2.2.2.2. Seeded Region Growing

To implement this algorithm, we first determine the initial seed points that are provided by the first step corresponding to the treetops (Section 2.2.1). The algorithm starts with the seed points that represent the starting points for region growth. The algorithm iteratively examines the neighboring pixels of the seed points/treetops and compares their properties to determine if they should be added to the growing region. The criteria for region expansion are typically based on similarity measures: Intensity, color, texture (Novotný et al., 2011). We implemented the algorithm in SAGA GIS (2.3.2) with a similarity threshold of 0.001. The result of the algorithm is a set of segments in TIF format. Then, we polygonise the segments to create a shapefile.

2.2.2.3. Thiessen polygons

Thiessen polygons (Voronoi polygons), is one of the most classical and old methods for the tree delineation. The initial step is to identify the tree points or crown centers. These points are obtained using the local maxima filtering in previous steps (section 2.2.1). The Thiessen polygon algorithm is then applied to the tree points. This algorithm divides the study area into polygons based on the proximity to the tree points. Each polygon represents the region closest to a specific crown center. Once the Thiessen polygons are generated, each tree point is assigned to the corresponding polygon based on its proximity. This means that any point within a particular thiessen polygon is considered part of the corresponding tree. (Argamosa et al., 2016). The algorithm was implemented in ArcGIS Version 10.8.1 (Esri. (2021).

2.3 Analysis and Evaluation

A subset of 11 infested trees was selected from a total of 36 infested trees in a representative sample (as they were in a similar stage of infestation by Bark Beetles, based on the field observation of symptoms). Similarly, an equal number of healthy trees (11 trees) with clearly observable healthy crowns were identified. Spectral information was then extracted from each of the crowns (11 healthy and 11

infested) delineated by the four (4) automatic ITCD methods. We extracted the spectra of the 5 individual bands and Vegetation Indices: NDVI (Normalized difference vegetation Index), GNDVI (Green Normalized Difference Vegetation Index), RENDVI (Rededge Normalized difference vegetation Index), ExG (Excess Green Index), and OSAVI (Optimized Soil Adjusted Vegetation Index), calculated using their respective formulas as shown in table. 2. To assess the significance between healthy and infested trees, a non-parametric Mann-Whitney test was used to compare differences between the two classes (infested and healthy), for each of the 4 automatic ITCD algorithms, as well as for the manual delineation. A statistical significance level of 0.05 (p-value) was employed for the analysis. If the p-value is less than the chosen significance level, it means there is a significant difference between the two classes. Then, the p-values obtained were compared across the 4 automatic ITCD methods and the manually delineated (reference) trees. These reference tree crowns were manually delineated in ArcGIS Version 10.8.1 (Esri, 2021) using the documentation photos captured during the fieldwork.

Vegetation Index	Formula
NDVI	$(\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red})$
GNDVI	$(\text{NIR} - \text{Green}) / (\text{NIR} + \text{Green})$
ExG	$2 * \text{Green} - \text{Red} - \text{Blue}$
RENDVI	$(\text{NIR} - \text{RE}) / (\text{NIR} + \text{RE})$
OSAVI	$(\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red} + 0.16)$

Table 2. Vegetation Indices formulas used in our study.

3. Results and Discussion

To evaluate our methods, we used two approaches: (1) assessing treetop locations, and the quality of tree crown delineation across different ITCD automatic methods, and (2) analysing the impact of automatic ITCD on reflectance (5 bands) and the chosen vegetation indices values when the tree health is affected during the green-to-yellow stage of infestation and their comparison with the reference (manually delineated) trees. Figure 4 illustrates the graphical results of the treetop detection and the different automatic ITCD methods. Our visual analysis shows that the 3-meter circular fixed window filter for local maxima detection in the CHM successfully identified most treetops in the study area. However, some challenges remained, including double treetop detections and the omission of smaller trees. Slight manual refinement was needed to improve treetop detection accuracy. The use of the fixed window size is computationally efficient and works well when trees are uniform in size and shape, as in our study. However, it may lead to the omission of small trees and reduced accuracy in heterogeneous forests. A window that is too small can miss large trees, while a too-large window may merge multiple smaller trees (Larsen et al., 2011). In contrast, an adaptive window size enhances detection accuracy by adjusting to individual tree sizes, though it may struggle in dense forests where overlapping trees obscure smaller ones (Chen et al., 2021). The visual assessment of the results of delineation algorithms (Figure 4) revealed notable differences, with the seeded

region growing algorithm providing the most accurate tree crown contours. This aligns with Miraki et al., 2021, who identified it as the most effective ITCD method in Hyrcanian broadleaf forests, and Dalponte et al., 2023, who found it highly effective for ALS data. Other algorithms have limitations: the buffer method works well in monocultures but oversimplifies crowns in mixed forests (Klouček et al., 2019), while Marker Controlled Watershed Segmentation suffers from over-segmentation and requires extensive parameter tuning and filtering to improve accuracy (Amiri et al., 2014).

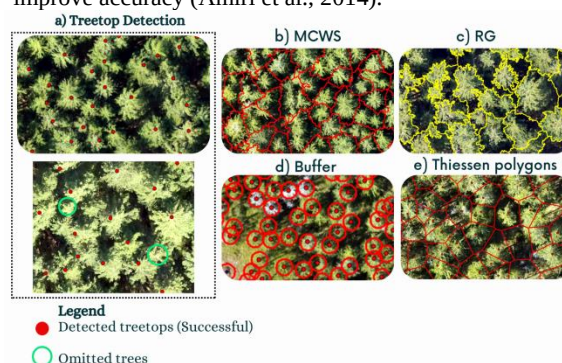


Figure 4. (a) Treetop detection, where red dots indicate successfully detected treetops, and green circles highlight example of missed detections by local maxima filtering.

(b) Crown delineation using MCWS. (c) Crown delineation using RG. (d) Crown delineation using buffer method. (e) Crown delineation using Thiessen polygons.

The study demonstrated the variability in the effectiveness of automatic ITCD algorithms for detecting early BB infestations (in the green-to-yellow stage). Figure 5 illustrates the relative reflectance of infested trees across five individual spectral bands and five vegetation indices for each of the 4 automatic ITCD methods, as well as the manual delineation. Although the differences are not significant, infested tree crowns (manually delineated) typically showed higher reflectance across all five bands compared to the automatically delineated crowns. For vegetation indices, infested tree crowns (manually delineated) had similar or lower values for NDVI, RENDVI, OSAVI, and GNDVI, with the exception of ExG, which was higher in the manually delineated crowns compared to the automatic methods.

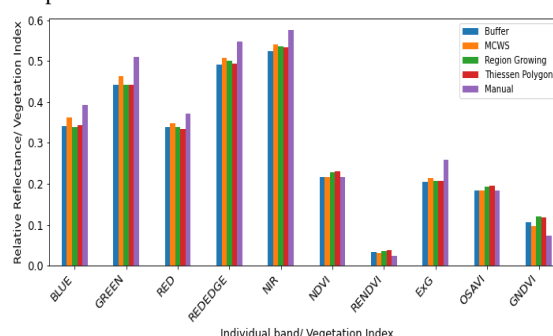


Figure 5. Relative reflectance of Infested trees across individual spectral bands and Vegetation Indices for automatic ITCD delineation and manual delineation methods. (MCWS: Marker-Controlled Watershed Segmentation)

Next, a statistical test (Mann Whitney) was conducted to compare healthy and infested trees, assessing their separability across both manually delineated crowns and

those identified by the 4 automatic ITCD algorithms. Figure 6 presents a heatmap depicting the spectral separability (between healthy and infested trees) for each delineation (4 automatic and manual) method across different spectral features. In general, the statistical analysis revealed no significant differences (p -value > 0.05) between healthy and infested trees in visible spectrum bands (Red, green and blue) for automatic ITCD methods and manual delineation. Still, important differences (p -value < 0.05) were found in the red-edge and NIR bands (Figure 6). As for vegetation Indices, NDVI, GNDVI, RENDVI, and OSAVI were statistically significant ($p < 0.05$) for distinguishing healthy and infested trees across the 4 ITCD automatic methods, with minimal sensitivity to delineation differences. Even when statistical significance between healthy and infested trees is not achieved (p -values > 0.05), the red spectral band in manual delineation has a lower p -value than automatic methods, suggesting a stronger distinction between healthy and infested trees. Meanwhile, ExG (between healthy and infested trees) lacked statistical significance in manually delineated trees (p -value > 0.05) but is significant in automatic ITCD methods, indicating greater sensitivity to infestation in automatically delineated crowns.



Figure 6. Heatmap of the spectral separability (between healthy and infested trees) for each delineation method (Automatic and manual) across different spectral features. (No sig: No statistical significance)

In our study, the automatic ITCD methods did not outperform the manual delineation in separating between healthy and infested trees; there were slightly minor differences, as opposed to the study conducted by Minařík et al., 2020, where the ITCD automatic methods had greater precision in feature extraction. Despite the non-statistical significance (p -value > 0.05), the red band, linked to chlorophyll absorption, showed stronger separability (between healthy and infested trees) in manual delineation, as it captures spectral infestation effects more clearly (most indicative of reduction in leaf pigments and chlorophyll). The importance of red wavelengths for the early detection of BB infestation was earlier proved in multiple studies (Bijou et al., 2023, Kautz et al., 2024). On the other hand, the ExG index is designed to enhance green vegetation but is highly affected by lighting, background soil, and shadows (Abdullah et al., 2017). In manual delineation, the lack of statistical significance between healthy and infested trees using this index (p -value > 0.05) may be attributed in our study to edge

effects capturing mixed pixels within tree crowns or the inclusion of background areas influenced by understory vegetation. These factors can alter ExG values and obscure differences between healthy and infested trees, highlighting the importance of effective background removal for detecting BB infestations. In contrast, automatic ITCD methods analyse more pixels, and may increase the statistical power and improve the detection of significant differences.

Considering the detection of early-stage BB infestations (during the green-to-yellow attack stage), methods like local maxima filtering with a buffer around the crown center may be ineffective. Using this method to extract the mean spectral signature of the crown may underestimate the level of infection compared to manually delineating visibly infested pixels, as it may include more pixels (healthy) that are irrelevant for analysis. In the early stage, analysing the spatial distribution of infested pixels within tree crowns is more effective than relying solely on mean crown values, given that the bark beetle infestation begins on the edges and spreads inward over time. On the other hand, advanced-stage infestations marked by dead branches/crown and more widespread visible symptoms within the crown (red and grey stages) may be more effectively identified using methods like region growing or Thiessen polygons, where the similarity/proximity threshold plays a crucial role in delineating a larger infested area of the crown. However, for bark beetles infestations, early detection is more important, as it allows foresters implementing timely sanitation measures in the field. From this experiment, we can suggest that replacing manual tree crown delineation with ITCD automatic methods may not always be suitable, particularly for early detection of BB infestation (Green stage). Automatic ITCD methods may not be able to detect spectral differences depending on the infestation level, bands, and indices used, while manual delineation, though subjective (despite potential human bias), can lead to under- or overestimation of infestation severity. Both automatic and manual delineations can be strongly influenced by the quality of the pre-processing (Background removal etc...). Temporal analysis of infested pixels through multitemporal imagery and ground observations is highly recommended for accurately assessing infestation progression. Therefore, expert knowledge, and careful field observations, remains the most reliable input for precise tree delineation and detection of early-stage bark beetle infestations. Despite advancements, applying ITCD algorithms to UAV imagery for forest health assessment remains challenging due to variations in forest type (e.g., mixed forests, monocultures), spatial resolution, pre-processing quality, infestation stage (in the case of BB attacks), parameterization, of different algorithms. Further research is needed to refine automatic ITCD methods and optimize their effectiveness for forest health monitoring (particularly for BB infestations). Future improvements could include integrating additional spectral bands and vegetation indices, analysing different infestation stages, and leveraging deep learning for object detection to enhance consistency across multiple study sites.

4. Conclusions

UAV-based Individual Tree Detection and Delineation (ITCD) have revolutionized forestry management by offering a more efficient way to map forests and assess tree health, including bark beetle infestations. Trees are

located and delineated using UAV imagery and advanced algorithms, reducing the reliance on time-consuming traditional methods (field surveys). The objective of this study was to evaluate the performance of four automatic ITCD algorithms in detecting early-stage BB infestations (green to yellow stage) in spruce forest, comparing them to manually delineated tree crowns, in the Krkonoše National Park, in the Czech Republic. The analysis focused on the assessment of the treetop detection and tree crown delineation quality, as well as the impact of these 4 automatic ITCD methods on differentiating healthy and infested trees, using reflectance values across five spectral bands and five vegetation indices. High-resolution UAV imagery (2 cm) captured by the DJI Phantom 4 Multispectral sensor, along with a derived CHM, was used to detect treetops through local maxima filtering. For tree delineation, four algorithms were applied: Buffer, marker-controlled watershed segmentation, Thiessen polygons, and seeded region growing. The results from these methods were compared with manually delineated tree crowns as a reference. The main conclusions of this experiment are:

- The results showed that the 3-meter circular fixed window filter for local maxima detection in the CHM successfully identified most treetops, although some challenges, such as double detections and missed small trees, were observed.
- The visual analysis of the automated ITCD algorithms revealed that the seeded region growing algorithm provided the most accurate tree crown delineation. Other methods like the buffer approach and Marker-Controlled Watershed Segmentation (MCWS) presented limitations, such as oversimplification of crowns and over-segmentation respectively.
- Statistical analysis confirmed that spectral bands in the red-edge and NIR regions, as well as the various vegetation indices, are useful for distinguishing between healthy and infested trees, although the statistical significance varied by each automatic ITCD method. The red spectral band proved to be particularly important in manual delineation, as it better captured chlorophyll reduction, a key indicator of BB infestation. In contrast, automatic ITCD methods showed higher sensitivity in detecting differences in ExG values between healthy and infested trees, highlighting the importance of proper background removal and algorithm optimization.
- This study suggests that while automatic ITCD methods offer computational efficiency, they may not be always suitable for early-stage BB infestation detection. Temporal analysis of infested pixels with multitemporal imagery may improve infestation detection accuracy by manually identifying the affected areas of the crown.
- Expert knowledge (of the infestation stage) and field observations (coordinates of tree locations and BB infestation symptoms) continue to be crucial for the precise delineation of tree crowns and accurate early-stage BB infestation detection.

Acknowledgements

The research was supported by Technology Agency of the Czech Republic – project no. SS05010124 “Assessment of the impact of land cover changes on local hydrology and climate in the Krkonoše Mts. National Park using remote sensing and hydrological modelling”, and – project no. SS07010417, “Earth observation technologies for the surveillance activities of the Czech Environmental Inspectorate”. Also, support was provided by the European Commission, CINEA Horizon Europe project no. 101081307 “Towards Sustainable Land-Use in the Context of Climate Change and Biodiversity in Europe (Europe-LAND)”.

References

- Abdullah, W. M. & Yaakob, S. N., 2017. Modified excess green vegetation index for uneven illumination. *Int. J. Curr. Res.* 9.
- Amiri, N., Hussin, Y.A.W., Tiejun, 2014. Assessment of marker-controlled watershed segmentation algorithm for individual tree top detection and crown delineation. *Fac. Geo-Inf. Sci. Earth Observation*.
- Argamosa, R. J. L., E. C. Paringit, K. R. Quinton, F. A. M. Tandoc, R. A. G. Faelga, C. A. G. Ibañez, M. A. V. Posilero, and G. P. Zaragosa., 2016. “Fully Automated GIS-Based Individual Tree Crown Delineation Based on Curvature Values from a LiDAR Derived Canopy Height Model in a Coniferous Plantation.” *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives* 41(July):563–69. doi: 10.5194/isprsarchives-XLI-B8-563-2016.
- Barnes, C., Balzter, H., Barrett, K., Eddy, J., Milner, S., & Suárez, J. C. 2017. Individual Tree Crown Delineation from Airborne Laser Scanning for Diseased Larch Forest Stands. *Remote Sensing*, 9(3), 231. <https://doi.org/10.3390/rs9030231>
- Bijou, S., Kupková, L., Potůčková, M., Červená, L., Lysák, J., 2023. Evaluation of the bark beetle green attack detectability in spruce forest from multitemporal multispectral UAV imagery. *ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci. X-1/W1-202*, 1033–1040. doi.org/10.5194/isprs-annals-X-1-W1-2023-1033-2023.
- Braga, G., Peripato, J.R., Dalagnol, R., Ferreira, P., Tarabalka, Y., Aragão, O.C., Velho, F.d.C., Shiguemori, E.H., Wagner, F.H., 2020. Tree crown delineation algorithm based on a convolutional neural network. *Remote Sens.* 12(8), 1288. <https://doi.org/10.3390/rs12081288>.
- Chen, S., Liang, D., Ying, B., Zhu, W., Zhou, G., Wang, Y., 2021. Assessment of an improved individual tree detection method based on local-maximum algorithm from unmanned aerial vehicle RGB imagery in overlapping canopy mountain forests. *Int. J. Remote Sens.* 42(1), 106–125. <https://doi.org/10.1080/01431161.2020.1809024>.
- Dalponete, M., Cetto, R., ...Frizzera, L., Gianelle, D., 2023. Spectral separability of bark beetle infestation stages: A single-tree time-series analysis using Planet imagery. *Ecological Indicators* 153. <https://doi.org/10.1016/j.ecolind.2023.110349>
- Diez, Y., Kentsch, S., Caceres, M.L., Nguyen, H., Serrano, D., & Roure, F., 2020. Comparison of Algorithms for Tree-top Detection in Drone Image Mosaics of Japanese Mixed

- Forests. International Conference on Pattern Recognition Applications and Methods. DOI: 10.5220/0009165800750087
- Freudenberg, M., Magdon, P. & Nölke, N. Individual tree crown delineation in high-resolution remote sensing images based on U-Net, 2022. *Neural Comput & Applic* 34,22197–22207. <https://doi.org/10.1007/s00521-022-07640-4>
- Honkavaara, E., Näsä, R., Oliveira, R., Viljanen, N., Suomalainen, J., Khoramshahi, E., Hakala, T., Nevalainen, O., Markelin, L., Vuorinen, M., Kankaanhuhta, V., Lyytikäinen-Saarenmaa, P., and Haataja, L. 2020: USING MULTITEMPORAL HYPER- AND MULTISPECTRAL UAV IMAGING FOR DETECTING BARK BEETLE INFESTATION ON NORWAY SPRUCE, *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.*, XLIII-B3-2020, 429–434, <https://doi.org/10.5194/isprs-archives-XLIII-B3-2020-429-2020>, 2020.
- Hu, B. and Jung, W.: INDIVIDUAL TREE CROWN DELINEATION FROM HIGH SPATIAL RESOLUTION IMAGERY USING U-NET, *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.*, XLIII-B3-2021, 61–66, <https://doi.org/10.5194/isprs-archives-XLIII-B3-2021-61-2021>, 2021.
- Kautz, M., Feurer, J., Adler, P., 2024. Early detection of bark beetle (*Ips typographus*) infestations by remote sensing – A critical review of recent research. *Forest Ecol. Manage.* 556, 121595. <https://doi.org/10.1016/j.foreco.2023.121595>.
- Klouček, T., Komárek, J., Surový, P., Hrach, K., Janata, P., Vašíček, B., 2019. The use of UAV mounted sensors for precise detection of bark beetle infestation. *Remote Sens.* 11(13), 1–17. <https://doi.org/10.3390/rs11131561>.
- Larsen, M., Eriksson, M., Descombes, X., Perrin, G., Brandtberg, T., Gougeon, F.A., 2011. Comparison of six individual tree crown detection algorithms evaluated under varying forest conditions. *Int. J. Remote Sens.* 32(20), 5827–5852. <https://doi.org/10.1080/01431161.2010.507790>.
- Lassalle, G., Ferreira, M. P., La Rosa, L. E. C. & de Souza Filho, C. R., 2022. Deep learning-based individual tree crown delineation in mangrove forests using very-high-resolution satellite imagery. *ISPRS J. Photogramm. Remote Sens.* 189, 220–235.
- Meyer, F., Beucher, S., 1990. Morphological segmentation. *Journal of Visual Communication and Image Representation* 1(1), 21–46. [doi.org/10.1016/1047-3203\(90\)90014-7](https://doi.org/10.1016/1047-3203(90)90014-7).
- Minařík, R., Langhammer, J., Lendzioch, T., 2020. Automatic Tree Crown Extraction from UAS Multispectral Imagery for the Detection of Bark Beetle Disturbance in Mixed Forests. *Remote Sensing* 12(24), 1–31. doi.org/10.3390/rs12244081.
- Miraki, M., Sohrabi, H., Fatehi, P., Kneubuehler, M., 2021, Individual tree crown delineation from high-resolution UAV images in broadleaf forest. *Ecol. Inform.* 61, 101207. doi.org/10.1016/j.ecoinf.2020.101207.
- Mohammed, Bouzkraoui. 1999. “Détection Des Arbres Individuels Dans Des Images de Haute Resolution.”
- Niemann, K.O., Quinn, G., Stephen, R., Visintini, F., Parton, D., 2015. Hyperspectral remote sensing of mountain pine beetle with an emphasis on previal assessment. *Can. J. Remote Sens.* 41(3), 191–202. doi.org/10.1080/07038992.2015.1065707.
- Novotný, J., Hanuš, J., Lukeš, P., Kaplan, V., 2011. Individual tree crowns delineation using local maxima approach and seeded region growing technique. *GIS Ostrava* 26(1), 23–26.
- Panagiotidis, D., Abdollahnejad, A., Surový, P., Chiteculo, V., 2017. Determining tree height and crown diameter from high-resolution UAV imagery. *Int. J. Remote Sens.* 38(8–10), 2392–2410. doi.org/10.1080/01431161.2016.1264028.
- Qiu, L., Jing, L., Hu, B., Li, H. & Tang, Y. 2020. A new individual tree crown delineation method for high resolution multispectral imagery. *Remote Sens.* 12, 1–20. <https://doi.org/10.3390/rs12030585>.
- Safonova, A., Hamad, Y., Dmitriev, E., Georgiev, G., Trenkin, V., Georgieva, M., Dimitrov, S., Iliev, M., 2021. Individual Tree Crown Delineation for Species Classification and Assessment of Vital Status of Forest Stands from UAV Images. *Drones* 5(3). <https://doi.org/10.3390/drones5030077>
- Shah, R., Hussin, Y. A., Schlerf, M. & Gilani, H. Comparison of individual tree crown delineation method for carbon stock estimation using very high resolution satellite images, 2011. 32nd Asian Conf. Remote Sens. 2011, ACRS 2011 2, 1311–1316.
- Sun, Y., Huang, J., Ao, Z., Lao, D. & Xin, Q. 2019. Deep learning approaches for the mapping of tree species diversity in a tropical wetland using airborne LiDAR and high-spatial-resolution remote sensing images. *Forests* 10.
- Tao, H., Li, C., Zhao, D., Deng, S., Hu, H., Xu, X., & Jing, W. , 2020. Deep learning-based dead pine tree detection from unmanned aerial vehicle images. *International Journal of Remote Sensing*, 41(21), 8238–8255. <https://doi.org/10.1080/01431161.2020.1766145>
- Yin, D., Wang, L., 2016. How to assess the accuracy of the individual tree-based forest inventory derived from remotely sensed data: a review. *Int. J. Remote Sens.* 37(19),4521–4553. doi.org/10.1080/01431161.2016.1214302.
- Zhen, Z., Quackenbush, L.J., Zhang, L., 2016. Trends in automatic individual tree crown detection and delineation—evolution of LiDAR data. *Remote Sens.* 8(4), 1–26. doi.org/10.3390/rs8040333.
- Zheng, J., Yuan, S., Li, W., Fu, H. & Yu, L, 2023. A review of individual tree crown detection and delineation from optical remote sensing images. 1–58. <https://doi.org/10.48550/arXiv.2310.13481>