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An Integrated Approach: Watershed Segmentation with Local Maxima and Minima Algorithms for Tree Crown Delineation of Mango (*Mangifera indica*) using UAV Multispectral Imagery

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ABSTRACT

Precision forestry and agriculture rely on precise tree crown delineation as a fundamental component for effective forest management activities. The selection of appropriate techniques and algorithms for tree crown delineation significantly influences the accuracy and reliability of the outcomes. This study was conducted in a mango plantation at Universiti Teknologi MARA, Arau, Perlis, employing Unmanned Aerial Vehicle (UAV) multispectral imaging. The focus is to assess the accuracy of tree crown delineation using two different algorithms, namely watershed segmentation and local maxima and minima. The conventional method was used for reference parameter derivation and tree positioning, while object-based image analysis was employed for processing the multispectral images. Additionally, a manual digitization approach was utilized to conduct an accuracy assessment of the resulting tree crown delineation. The study findings indicated that the watershed algorithm exhibited superior accuracy, achieving 83.3% total 1:1 match and 73% goodness of fit, compared to the local maxima and minima algorithm, which yielded 81.7% and 71%, respectively. These results hold significant implications for forest management planning and remote sensing-based forest quantification estimation, enabling the development of efficient and effective forest management strategies for the future.

Keywords:
Tree crown delineation; multispectral imaging; watershed segmentation; local maxima and minima; remote sensing

1. Introduction

Harumanis mango (*Mangifera indica*) is a highly valued tropical fruit, known for its unique characteristics and high demand in the market. This special breed of mango is grown exclusively in Perlis, Malaysia, and is harvested once a year during its season [1]. The quality of the mango is

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attributed to its vibrant green skin with yellow dots, which retains its colour even when ripe, and its aromatic fragrance and sweet taste are the result of lower rainfall distribution and abundant sunshine [2]. The production of high-quality Harumanis mangoes depends on several factors, including weather conditions and natural ecology. The weather must be hot and dry during the day and cold and windy at night for a continuous three-month period for healthy flowering and fruit-bearing. Frequent rainfall throughout this period can negatively affect fruit production [3]. Harumanis mangoes in Perlis are usually ripe for picking from late April to mid-June, typically around 60 to 120 days after flowering or approximately 8 weeks after the fruits reach a diameter of about 4 cm.

Individual Tree Crown (ITC) identification is an important technique for forestry and precision farming, which enables a precise delineation of individual trees and their crown boundaries, particularly for forest management, field inventory, and biodiversity assessments [4,5]. Previously, the conventional approach was utilized for the collection of data concerning tree positioning and various tree parameters, including tree crown, diameter at breast height and tree height. According to the research conducted by Chave *et al.,* [6] this traditional method of acquiring data on tree parameters demands a significant amount of labour, intricate sampling designs and additional efforts. This is exemplified by the manual collection of tree crown data, which necessitates the data collectors positioning themselves beneath the tree. However, in current practices, tree crown delineation is increasingly being facilitated using various algorithms, such as the watershed and local maxima and minima algorithms, which rely on high-resolution multispectral imagery obtained from unmanned aerial vehicles (UAV) [4].

Therefore, the purpose of this study is to investigate the tree crown delineation of Harumanis plantations in Perlis, Malaysia, using UAV multispectral and object-based image analysis (OBIA). The objectives of this study include (1) establishing the data collection of Harumanis tree parameters, such as diameter at breast height (DBH), tree height and tree crown diameter; (2) performing the tree crown delineation using the watershed algorithm and local maxima and minima; and (3) producing the tree crown delineation map of Harumanis crops in the study area. The use of UAV multispectral imagery and OBIA technique is expected to provide accurate and efficient tree crown delineation for Harumanis plantations. The accuracy assessment between the watershed algorithm and local maxima and minima will be performed to validate the results. This study's findings will contribute to the development of precision farming techniques for Harumanis mango production and forest management in the region.

2. Study Background

2.1 Tree Crown Delineation Techniques

Individual tree crowns (ITCs) are fundamental components of precision forestry and agriculture [4]. They serve as a crucial link connecting diverse tree measurements, including crown shape, gathered from various data sources [5]. This process involves the identification and outlining of tree canopy boundaries. Accurate tree delineation and detection play a pivotal role in precision forestry and agriculture, providing essential information for a range of applications, such as mapping, stand density assessment, height distribution analysis, estimating average crown size, determining stem diameter distribution, calculating leaf area index, evaluating biomass stock, and monitoring growth [11]. Moreover, this information empowers foresters to enhance forest management practices and field inventories, including selective cutting, silviculture treatments, and biodiversity assessments [5]. Leveraging remotely sensed data enables the comprehensive acquisition of detailed tree information across extensive areas, facilitating the derivation of these essential metrics [11]. Furthermore, the ability to identify trees from high-resolution aerial images based on crown shape and structure proves beneficial for estimating forest density and implementing fire prevention measures [13]. Timely identification of potential threats to tree populations allows for proactive intervention strategies, preserving forest ecosystems and ensuring sustainable resource management.

2.2 Crown Projection Area

The crown projection area (CPA), representing the vertical projection of tree crowns onto the ground surface, plays a crucial role in quantifying biomass volume and assessing inter-tree competition dynamics [14]. Accurately measuring tree crowns can be challenging due to the natural variability in their shapes. However, a practical method involves vertically projecting the crown perimeter onto the ground, utilizing the average diameter obtained from two perpendicular orientations [9]. Moreover, advancements in remote sensing technologies, including multispectral imagery, have significantly enhanced the precision of CPA measurements. Multispectral technology provides detailed information about tree canopies in multiple spectral bends, enabling the precise calculation of CPA and other tree-related parameters [15]. This technology has transformed forest inventory and management by allowing for large-scale, high-resolution data collection. Additionally, CPA serves a broader purpose than just estimating biomass. It plays a significant role in forestry research, helping researchers understand forest structure and dynamics. By analyzing variations in CPA across different tree species and sizes, researchers can gain insight into forest health and the distribution of resources such as light and nutrients [16]. Significantly, CPA demonstrates a correlation with tree diameter at breast height (DBH), facilitating the prediction of DBH for carbon estimation through suitable calculations. This relationship becomes particularly pivotal when modelling tree diameter using CPA data [9].

2.3 Tree Parameters

The diameter at breast height (DBH) serves as the primary measurement utilized by tree professionals for tree characterization. DBH represents the diameter of a tree's trunk at a standardized height of 1.3 meters above the ground. The tree diameter can be efficiently determined by employing a specifically calibrated diameter tape, commonly referred to as a d-tape, which provides a direct measurement of the circumference that corresponds to the diameter. Alternatively, in the absence of a d-tape, a string, measuring tape, thumbtack, and calculator can be used as suitable substitutes for measuring the tree's diameter [17]. Tree height, in the realm of forestry, represents the vertical distance from the base of the tree to the highest point of its foliage. It is a metric of utmost importance, critical for a comprehensive understanding of a tree’s growth and ecological impact. Accurately measuring tree height can be challenging and should not be confused with the length of the tree trunk, as the two can significantly differ, especially in cases where a tree may incline or have an irregular shape. In such instances, the trunk length may exceed or fall short of the tree’s actual height, making precise measurements even more challenging [18].

To address this complexity, a range of specialized instruments and methodologies have been developed to accurately measure tree height, customized to the specific conditions and characteristics of the tree and its surrounding environment. Among these, several trigonometric devices, such as Blume Leiss, Vertex, or Criterion are available to researchers for height measurements, with the selection of the instrument dependent on various factors, including stand density and crown visibility [17]. The most straightforward method for measuring tree height involves utilizing a telescoping height measuring pole, allowing the assessor to elevate a pole of known length to the same level as the tree's uppermost point. However, this method is commonly employed for measuring smaller trees, where the pole's length can effectively match the tree's height. In the case of larger trees, a more practical approach involves the use of a lightweight handheld instrument designed to assess the tree height from a distance, ensuring both accuracy and safety during the measurement process [18].

2.4 Object-Based Image Analysis in Forestry

Object-based image analysis (OBIA) is an advanced technique that has emerged as a promising solution to overcome the limitations associated with pixel-based approaches. OBIA is recognized for its ability to deliver highly accurate results [19]. It leverages spectral, textural, and contextual information to identify thematic classes within an image. The key components of OBIA encompass image segmentation, feature extraction, and classification process [20]. The initial stage of OBIA involves segmenting the image into homogeneous objects, a critical task that sets the foundation for subsequent analysis. For this purpose, various algorithms, such as watershed, local maxima and minima, and region growing algorithms, are employed. Each of these algorithms has a distinctive role in defining objects within the image. They use inherent statistical properties derived from the individual pixels to guide this process. The accuracy of the classification process strongly relied on the quality and precision of image segmentation [20]. Therefore, image segmentation plays an important role within the OBIA framework. Upon completing segmentation and classification, a refinement process is typically employed to purify the delineated objects by eliminating impurities or undesirable elements. This stage ensures that the delineation process aligns closely with the true characteristics of the objects of interest. Collectively, segmentation, classification, and refinement form the essential steps involved in tree crown delineation [21]. In the context of this study, OBIA software was utilized, which facilitated the generation of tree crown boundaries and the determination of maximum tree heights.

2.4.1 Watershed segmentation algorithm

The Watershed transformation algorithm is a powerful method employed for separating image objects and features within imagery datasets. This method is particularly effective in handling the complex task of distinguishing overlapping tree crowns, which is achieved by setting a threshold based on the average crown size observed in the study area [8]. The algorithms identify connection points, like watersheds in geography, to address the challenge of overlapping crowns, allowing researchers to differentiate individual trees within densely clustered arrangements [9]. Inspired by the concept of natural watersheds, the algorithm treats pixel values as if they represent topographical elevations, helping it segment the entire image into distinct catchment areas. It creates zones of influence around each local minimum, resembling the way water flows in landscapes. This analogy between topography and tree crown surfaces makes the watershed segmentation approach a widely accepted and effective technique for accurately delineating tree crowns [10]. The Watershed algorithm interprets pixel values as elevations, aiding precise delineation of tree crowns in dense forests.

2.4.2 Local maxima and minima algorithm

The local maxima method is widely employed for individual tree detection due to its simplicity and computational efficiency [11]. In this method, a moving window is employed to systematically identify the highest digital number value within an image, which subsequently serves as the central point for delineating the tree crown. In contrast, local minima are utilized to detect the valleys between trees, aiding in the accurate delineation of crown boundaries. The process of estimating tree crowns through the relative positions of local maxima and minima is grounded in two key assumptions. Firstly, it assumes that local maxima are consistently positioned within the crown area of individual trees. Secondly, it suggests that local minima occur at the crown's boundary within forested areas [12]. Previous studies have employed specific fixed window sizes, such as a circular window of 7x7 pixels for the local maximum filter and a square window of 3x3 pixels for the local minimum filter. The moving window approach is then set into motion, systematically traversing the entire image, and identifying the maximum and minimum values in accordance with the defined window sizes [11].

3. Methodology

3.1 Study Area

This study was conducted at plot B of the Harumanis plantation, situated within the UiTM Arau Campus in Perlis, with geographical coordinates at approximately latitude 6°26'44.50584"N and longitude 100°16'30.27318" E. The study area spans a total land area of approximately 2.63 hectares and is characterized by an elevation of 38.28 meters, as depicted in Figure 1. The climatic conditions within this region are favourable for the growth of harumanis mango, with an average annual rainfall of 1952mm and an average annual temperature of 26.8°C. Furthermore, the study site offers an open expanse that facilitates Global Navigation Satellite System (GNSS) observations and drone flights, enabling the collection of accurate spatial data for analysis and evaluation purposes.

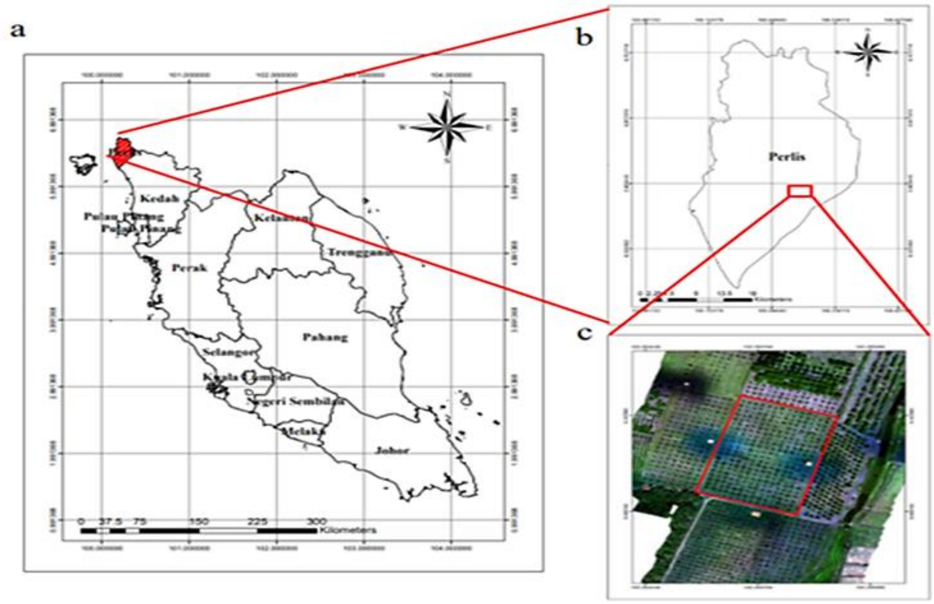


Fig. 1. Map of the study area (a) Map of Peninsular Malaysia (b) Map of Perlis (c) UAV multispectral image of Harumanis Plantation, UiTM Perlis

3.2 Ground Control Point (GCP) Establishment

Prior to UAV flight, the establishment of Permanent Ground Control Points (GCPs) is essential, following the static method of data collection. In this study, seven (7) GCPs were strategically positioned around the site, as depicted in Figure 2. The selection of GCP locations involved careful surveying, considering factors such as avoiding tractor routes and ensuring unobstructed visibility of the sky by at least 10-15%, while also avoiding any potential sheltering by trees. After GCP installation, network design was conducted in advance of data collection, ensuring that the lines of other GCPs from different sessions did not intersect. Additionally, it was ensured that the network design for each session did not form a closed shape. The Global Positioning System (GPS) observations were performed using the static positioning method with the utilization of Topcon GR-5 equipment. The GPS data collection comprised four (4) sessions, encompassing the measurement of seven (7) GCPs and two (2) nearby benchmarks. For each GCP in each session, three (3) epochs were recorded, with each epoch lasting 30 minutes. The collected data was then processed, incorporating the Real-Time Kinematic (RTK) data from Langkawi and Arau, which were connected to GCP 1 and GCP 3, respectively. The establishment of the GCPs as known reference points ensures the preservation of image integrity, allowing accurate alignment of the image coordinates with the corresponding locations on the Earth's surface.

Fig. 2. GCPs location [22]

3.3 Multispectral Image Acquisition

In this study, the UAV multispectral imagery was employed to facilitate the creation of tree crown delineation maps using the watershed, local maxima, and local minima algorithms. The UAV multispectral image acquisition was carried out during the afternoon to ensure the absence of tree shadows, as their presence can introduce complexities during the segmentation and classification processes. The Ardupilot quadcopter was selected as the designated drone model for image capture. Before the flight, flight planning was conducted, specifying a horizontal and vertical overlap of 75%, an altitude of 75 meters, and a spatial resolution of 5cm ground sampling distance (GSD). The drone was flown over the Harumanis plantation, encompassing an approximate area of 24.957 hectares. In addition to capturing RGB imagery, the drone was equipped to capture infrared data. It is noteworthy that the drone's flight coverage extended beyond the study area to encompass the entire region where the GCPs were located. In this work, the application of UAV itself has demonstrated it's ability to enhanced productivity while offering a reliable substitute for the meticulous ground survey techniques [23]. Figure 3 visually illustrates the UAV-derived image, utilizing the band combination of 3 (red), 4 (green), and 2 (blue).

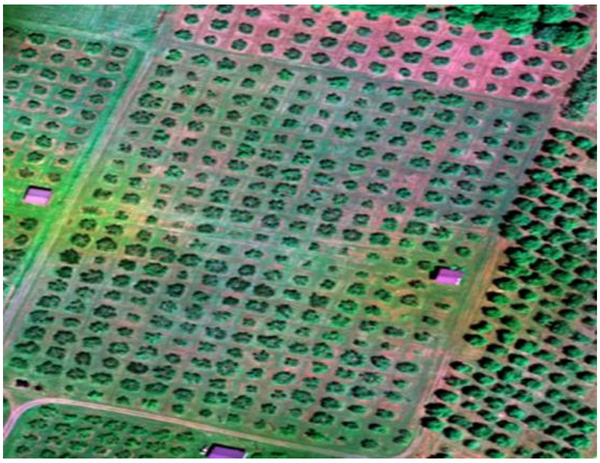


Fig. 3. UAV multispectral image

3.4 Measurement of Tree Parameters

The selection of trees for parameter measurement focused specifically on those with a diameter at breast height (DBH) exceeding 10cm, resulting in a total of 60 trees labelled with IDs ranging from 921 to 980. DBH measurements were obtained from trees utilizing a diameter tape, where the circumference of the tree trunk was encircled at a height of 1.3 m to determine the DBH. On the other hand, to retrieve the height of a tree, a Distometer device was employed, enabling measurements from the ground to the highest point of the tree's foliage. In relation to tree crown measurements, tape was employed. Two individuals were involved in the process, with one positioned beneath the tree on the right side, holding the tape and estimating its position at the tip of the leaf. Simultaneously, the other person stood in the opposite direction, conducting the same procedure. The collected tree crown data serves as a reference for the subsequent tree crown delineation process using OBIA software, facilitating a comparative evaluation of the accuracy between the watershed, local maxima and local minima algorithms.

3.5 Positioning of Selected Trees

A traverse survey was conducted to determine the positions of the selected trees. Prior reconnaissance was undertaken to strategically plan the traverse, ensuring that trees with designated IDs were visible from the traverse stations. A total of eight (8) stations were established along the traverse path, commencing at GCP 5 as the initial station and utilizing GCP 2 as the back bearing reference. The traverse is continuous around the study area where the tree with ID can be seen. Given the availability of permanent GCPs with known coordinates at GCP 2 and GCP 5, these coordinates were used as a basis for transferring coordinates at each traversed station. To calculate the coordinates, the Bowditch method was employed for coordinate transfer. However, due to the arrangement of harumanis trees, it was challenging to determine the positions of the trees without establishing new stations. Since the harumanis trees were planted in a structured manner, new stations were established to capture the positions of trees that were not visible from the traverse stations. These additional eight (8) stations were established to ensure comprehensive data collection. To determine the coordinates of each tree, the coordinates obtained from the GCPs were transferred to each established station, including the respective tree with its designated ID. The initial coordinates obtained from the GCPs were in the GDM2000 projection, necessitating a transformation to the Cassini-Soldner Malaysia projection. This transformation was performed to accurately compute and transfer the coordinates to the stations and trees. Subsequently, the coordinate projection was adjusted to WGS1984 to align with the projection of the UAV multispectral imagery, ensuring compatibility for further analysis and processing.

4. Data Processing

4.1 Processing of Ground Control Points (GCPs)

The GCPs were processed using Trimble Business Center (TBC) software. The dataset consists of seven (7) GCPs as depicted in Figure 4, which necessitated four (4) sessions for data collection. Within each session, three (3) epochs were recorded for each GCP. To enhance the accuracy of the processing, the GCP data will be merged with Real-Time Kinematic (RTK) data and benchmark measurements. This integrated approach ensures a higher level of precision. The GCP data will be processed individually, considering their respective sessions. Figure 5 depicts the network design of Ground Control Points (GCPs) utilized in this study. The first session, represented by the purple line, involves GCPs 7, 4, 1, and 5. The second session, indicated by the green line, comprises GCPs 5, 2, 3, and 6. GCPs 3, a benchmark located at the highway, 6 and 7 forms the third session, visualized by the yellow line. Lastly, the red line represents the last session, encompassing GCPs 7, 2, 4, and Benchmark Muda Agricultural Development Authority (MADA). To ensure the collection of highly accurate data, GCP 1 is connected to Real-Time Kinematic (RTK) data from Langkawi, while GCP 3 is connected to RTK data from Universiti Utara Malaysia (UUM). Multiple baselines are established for each GCP since three epochs are conducted within each session. Consequently, it becomes necessary to select a single baseline and deactivate the remaining lines. The GCP points will be merged into a single point, as there is redundancy due to multiple measurements of certain GCPs. This approach proves beneficial when assessing network accuracy and correctness.

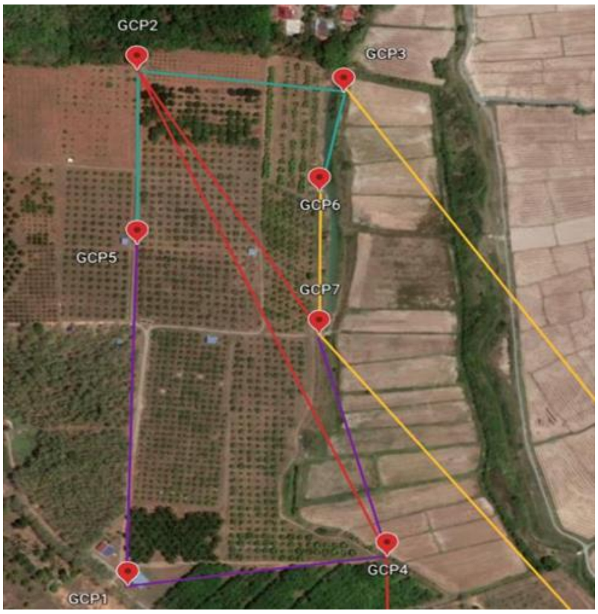


Fig. 4. Network design of GCPs

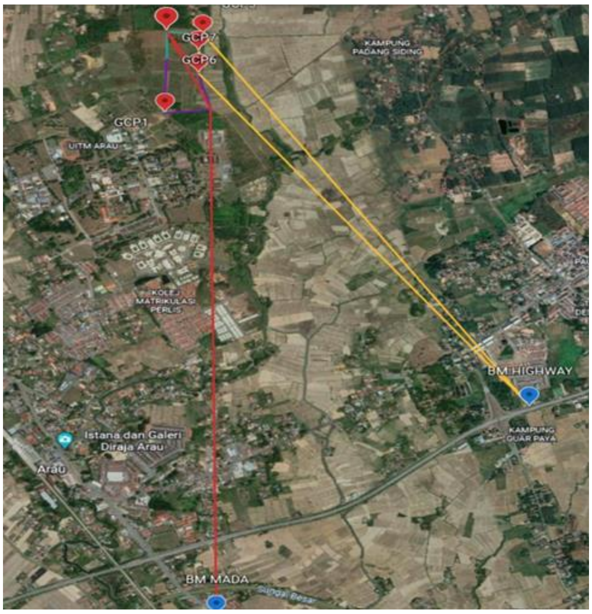


Fig. 5. Network design of GCPs and benchmarks [2]

Table 1 presents the GDM2000 projection coordinates of the Ground Control Points (GCPs), which were determined through the processing of TBC. Notably, the GCPs exhibit a negligible disparity in latitude and longitude due to their close spatial proximity. The variations in latitude and longitude between each GCP are minimal, with differences of merely seconds, as shown in Table 1. To verify the accuracy of the GCP coordinates derived from the TBC, the obtained coordinates were inputted into ArcMap software, in which all the seven (7) GCPs are impeccably positioned and aligned closely with their corresponding ground control points, indicating the correctness of the derived GCP coordinates.

Table 1
GCPs coordinate

GCP	Latitude	Longitude
GCP 1	6°27'13.46543"N	100°16'56.3934"E
GCP 2	6°27'33.50170"N	100°17'01.79160"E
GCP 3	6°27'31.15680"N	100°17'08.43449"E
GCP 4	6°27'11.64536"N	100°17'05.11409"E
GCP 5	6°27'26.44288"N	100°17'00.00586"E
GCP 6	6°27'26.43963"N	100°17'06.56725"E
GCP 7	6°27'21.15630"N	100°17'05.00184"E

4.2 Object-Based Image Analysis (OBIA)

The orthomosaic image obtained from the UAV multispectral data will undergo processing using the Object-Based Image Analysis (OBIA) technique. This technique involves three essential steps: segmentation, classification, and refinement. In the segmentation step, the image is partitioned into distinct objects representing land-based features. Subsequently, in the classification step, these objects are categorized based on their spatial, spectral, shape, and size properties. Lastly, the refinement step aims to eliminate impurities or unwanted elements through the extraction process. To accomplish tree crown delineation, two OBIA algorithms will be employed, namely the watershed algorithm and the local maxima and minima algorithm. The combination of these algorithms, integrated within the OBIA framework, enables the accurate delineation of tree crowns by effectively segmenting, classifying, and refining the objects within the orthomosaic image.

The segmentation process involves specifying a scale parameter of 50, which determines the size of image objects. A larger scale parameter results in larger objects, while a smaller scale parameter produces smaller objects. The UAV multispectral image consists of six layers, namely Red, Blue, Green, Near-Infrared (NIR), RedEdge, and Composite. Weightage values of four are assigned to the NIR layers, while the remaining layers are assigned a weightage value of one. Increasing the weightage of certain layers in the heterogeneity measure influences the merging of pixels or objects during the classification phase. Homogeneity criteria for shape and compactness are set to 0.8 and 0.5, respectively. The higher shape value emphasizes shape characteristics during segmentation, while the compactness value achieves a balanced consideration between compact and non-compact object segments. The range is searched based on the layer bands and will be used for subsequent classification, distinguishing four classes: tree crown, shadow, bare soil, and grass.

The classification step assigns the four predetermined classes: shadow, tree crown, bare soil, and grass to the image objects. Following class assignment, the merge region technique, also known as masking, is applied to merge objects within each class. This process is crucial for aggregating small pixels into larger segments, facilitating subsequent refinement. Refinement encompasses three main processes: individual tree separation, tree smoothening, and object removal. Individual tree separation involves utilizing the watershed and local extrema algorithms. The local extrema algorithm identifies areas that meet certain local maximum or minimum conditions within a defined domain and search range around the object. The watershed algorithm is employed without the local extrema algorithm. Subsequently, tree segments are subjected to smoothening to address non-circularity issues. Lastly, object removal is performed to address misclassified features detected during the process, employing predefined rules and suitable range selection.

4.3 Manual Digitization for Accuracy Assessment

Figure 6 depicts the image of manually digitized tree crown delineation. Manual digitization served as the reference for comparison against the results obtained using the algorithmic approaches. The manual digitization process involved the use of ArcMap software to accurately outline the boundaries of the tree crowns. It is important to note that the results obtained through manual digitization may differ from those obtained using algorithmic approaches, such as the watershed and local extrema algorithms. The manual digitization specifically focused on delineating the tree crowns of the selected trees used in the study.

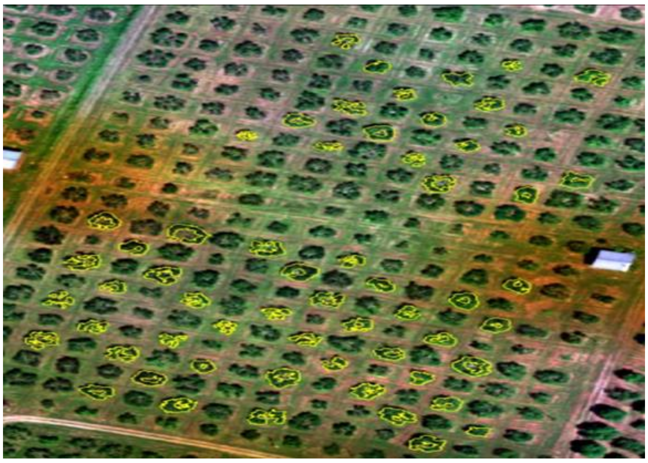


Fig. 6. Manual digitizing of tree crown delineation

5. Results and Discussion

5.1 Descriptive Analysis for Tree Parameters

A total of 60 Harumanis trees were selected for inclusion in the study based on a specific criterion, in which the minimum diameter at breast height (DBH) threshold of 10cm. The descriptive statistics of the tree sampling are shown in Table 2.

Table 2
Descriptive statistics of tree sampling

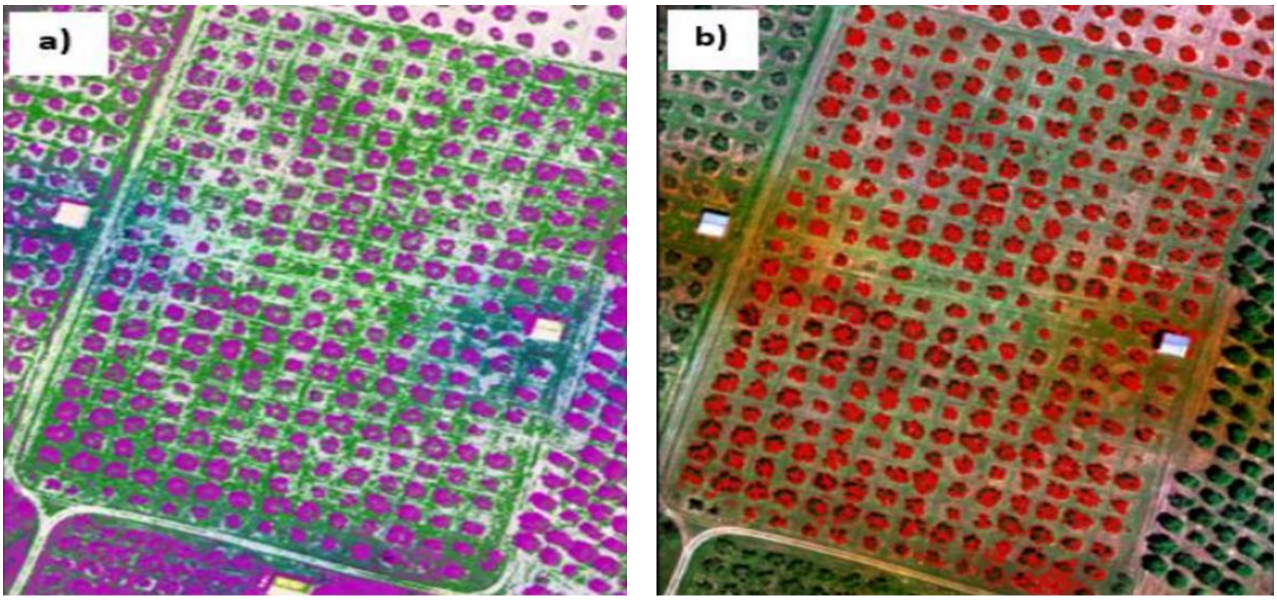
	DBH	Height	Tree Crown
Standard error of the mean	0.393	0.072	0.148
Minimum	11.000	2.11	3.600
Maximum	26.600	4.271	9.610
Mean	18.983	2.983	6.303
Standard Deviation	3.047	0.556	1.145

5.2 Tree Crown Delineation Using Watershed Algorithm

The process of creating tree crown delineation using the watershed algorithm involves following a four-step ruleset consisting of segmentation, classification, refinement, and removal of undesired objects. The employed segmentation algorithm in this study is multiresolution segmentation, which is crucial for accurate tree crown delineation. The selection of an appropriate scale parameter is essential, as higher values lead to the segmentation of larger object segments, while lower values result in smaller object segments. In this analysis, a scale parameter of 50 was chosen to achieve more precise classification outcomes. Furthermore, the weights assigned to each image layer are significant factors affecting the heterogeneity measure, which determines the merging of pixels or objects and subsequently influences the classification process.

Four distinct classifications were created: Shadow, Tree crown, Bare soil, and Grass. The objective of classification is to ensure that the segmented tree crowns do not include unwanted classifications, such as tree branches or other non-relevant features. Specific ranges were established for each classification based on the corresponding image layer. For example, the Shadow classification utilized the Brightness layer with a range of 5,000 to 21,000, while the Tree crown classification was based on the red layer within the range of 1,000 to 13,000. The Grass classification employed the Mix Diff layer with a range of 1.3 to 1.6, and the Bare soil classification utilized the red layer within the range of 2,600 to 50,000.

Additionally, a merge region function was applied to combine segments within each class, resulting in the enlargement of the segmentation scale parameter. The subsequent step, refinement, involved the separation of individual trees using the watershed algorithm to ensure that each tree's segmentation was distinct. Morphology techniques were then employed for tree smoothening, aiming to achieve more realistic, rounded shapes resembling actual trees in real-world scenarios. Finally, undesired objects that did not align with the assigned classifications were removed. The output of the tree crown segmentation was exported as a shapefile. Figure 7 illustrates the results of tree crown delineation using the watershed algorithm, displaying a) the tree crown delineation in OBIA software, and b) the exported tree crown delineation overlaid with the UAV multispectral image in ArcMap software.

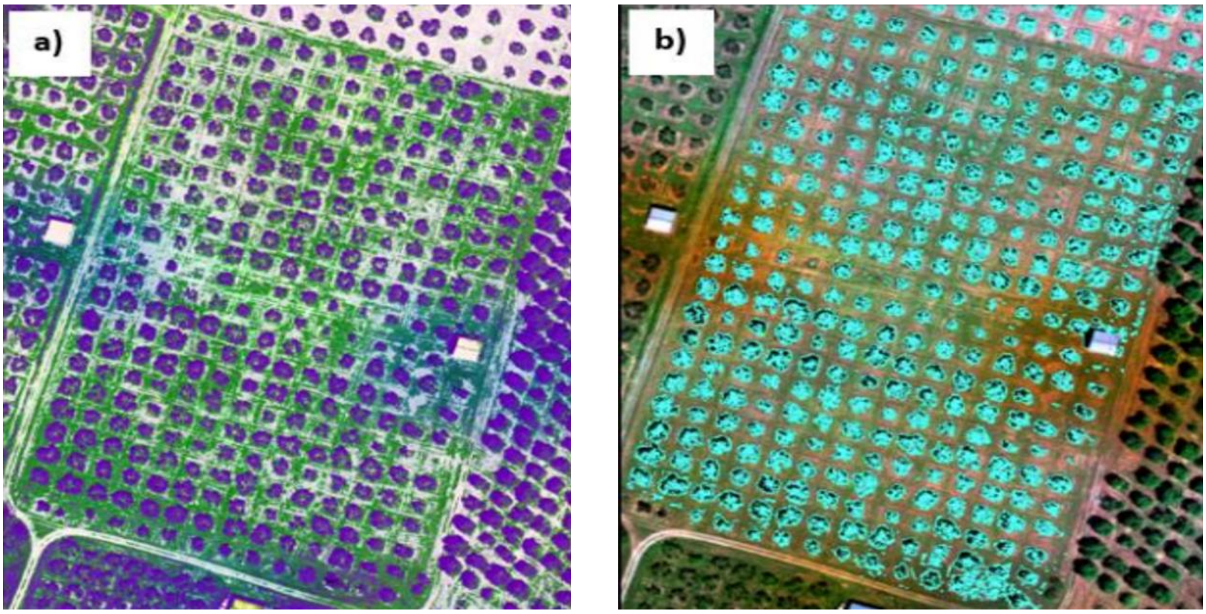


(a) (b)

Fig. 7. Tree crown delineation using watershed algorithm (a) Segmentation in OBIA software (b) Segmentation in ArcMap software

5.3 Tree Crown Delineation Using Local Maxima and Minima Algorithm

The ruleset employed to apply the local maxima and minima algorithm consists of three distinct steps, namely segmentation, classification, and refinement. In the segmentation step, the multiresolution segmentation technique is utilized, employing a scale parameter set to 50. Additionally, the image layer weights are configured as 1,1,4,4,1,1, with the higher weight of four (4) assigned to the NIR and Green layers. These parameters aim to achieve accurate segmentation of the image data. The classification stage involves assigning four (4) distinct classes to the image data. The Shadow class is determined based on the Brightness layer, with a range spanning from 5,000 to 21,000. The Tree Crown class is identified using the red layer, within a range of 1,000 to 13,000. The Grass class is determined through analysis of the Mix Diff layer, with a range of 1.3 to 1.6. Lastly, the Bare Land class is identified based on the red layer, with a range spanning from 2,600 to 50,000. Refinement of the segmentation results involves the insertion of two (2) child processes, namely local maxima and local minima, which enable the identification of areas exhibiting local maximum and minimum conditions. Subsequently, like the watershed algorithm, the resulting tree crown delineation is exported as a shapefile. Figure 8 showcases the outcome of the local extrema algorithm for tree crown delineation, with subfigure a) presenting the delineation in OBIA software and subfigure b) displaying the exported shapefile layered with the UAV multispectral image in ArcMap software.



(a) (b)

Fig. 8. Tree crown delineation using local extrema algorithm (a) Segmentation in OBIA software (b) Segmentation in ArcMap software

5.4 Analysis of Crown Projection Area

The CPA was conducted on a dataset consisting of 60 tree crowns. A manual digitization process collectively covering an area of 1282.719544 m^2. The area measurements exhibited a standard deviation of 7.346676. The results showed that within the CPA range of 41 to 50 m^2, no trees were observed, while the highest frequency of 29 trees was found within the CPA range of 21 to 30 m^2. For Watershed algorithms, the total area encompasses 1444.205803 m^2. The calculated standard deviation for the tree crown areas is 7.938860. The results indicate that the minimum frequency observed is one (1) tree within the CPA range of 0 to 10 m^2, while the highest CPA range for the watershed algorithm is 21 to 30 m^2, exhibiting a frequency of 26 trees. The local extrema algorithm was employed to analyze a dataset with a combined area of 1357.36698 m^2. The standard deviation of the tree crown areas is calculated to be 7.479397. The results indicate that the minimum frequency observed is one (1) tree within the CPA range of 0 to 10 m^2. Moreover, the largest CPA ranges for the local extrema algorithm are 11 to 20 m^2 and 21 to 30 m^2, with a frequency of 24 trees.

The comparison of CPA reveals that the most frequently observed ranges for the manually digitized, watershed algorithm, and local extrema algorithm are within the range of 21 m^2 to 30 m^2, with frequencies of 29, 26, and 24 trees, respectively. Notably, the local extrema algorithm exhibits high frequencies in two ranges: 11 m^2 to 20 m^2 and 21 m^2 to 30 m^2, with a frequency of 24 trees. The graphical representation demonstrates that the CPA values obtained from the watershed algorithm closely resemble those derived from manually digitized tree crown delineation. Upon comparing the total area covered by the manual digitized method and the algorithms, a disparity of 161.486259 m^2 is observed between the manual digitized and watershed algorithm methods, while a difference of 74.647436 m^2 is noted between the manual digitized and local extrema algorithm methods. This divergence can be attributed to the local extrema algorithm's tendency to segment numerous hollow areas, resulting in misclassifications where certain parts of the tree crown are identified as non-tree crown elements, as depicted in Figure 9. The figure illustrates tree ID 970, where the red line represents the watershed algorithm's delineation, and the cyan line represents the local extrema algorithm's delineation. The watershed algorithm achieves a more accurate segmentation by capturing the tree crown boundaries more effectively.

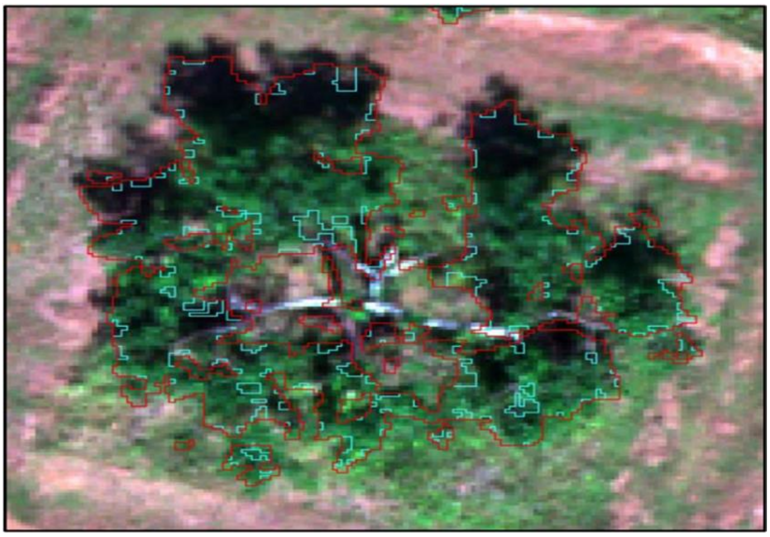


Fig. 9. Segmentation of watershed algorithm in red line and local extrema algorithm in cyan line

To conduct an accuracy assessment, it is necessary to calculate the CPA for both the watershed algorithm and the local extrema algorithm. Additionally, the intersection of CPA values between the watershed algorithm and the manual digitized method, as well as between the local extrema algorithm and the manual digitized method, needs to be determined. These calculations will involve the application of formulas for over-segmentation, under-segmentation, and distance index. Subsequently, a comparative analysis between the two distinct OBIA techniques will be conducted, providing insights into their respective performance and accuracy.

5.5 Comparative Analysis of Delineation Algorithms

The watershed algorithm and local extrema algorithm employ distinct step rulesets to achieve tree crown delineation. The watershed algorithm encompasses four crucial steps, while the local extrema algorithm involves three steps. Notably, the refinement stage of the watershed algorithm incorporates morphology and the removal of undesired objects, which are absent in the local extrema algorithm due to its advanced classification technique. The omission of these steps in the local extrema algorithm can potentially result in the exclusion of certain tree crown delineations. Both algorithms produce tree crown delineations that are exported as shapefiles and subsequently integrated into ArcMap software for the calculation of CPA. The CPA serves as an assessment metric to determine the algorithm's accuracy performance. To evaluate the precision of each algorithm, manual digitization of tree crown delineation was conducted, enabling the calculation of CPA for comparison with the algorithm-derived CPAs. The manually digitized tree crown delineation was then intersected with the algorithm-generated delineations to evaluate their resemblance to the reference tree crown.

Figure 10 illustrates the tree crown delineations obtained from different methods. Image (a) represents the manually digitized tree crown delineation, image (b) displays the tree crown delineation produced by the local extrema algorithm, and image (c) showcases the tree crown delineation generated by the watershed algorithm. The figure reveals that both algorithms exhibit classification inconsistencies. Specifically, the local extrema algorithm misclassifies shadows and grass as tree crowns, while the watershed algorithm solely misclassifies shadows. Furthermore, the figure indicates that the tree crown delineation derived from the watershed algorithm demonstrates a closer similarity to the manually digitized tree crown delineation compared to the delineation obtained from the local extrema algorithm.

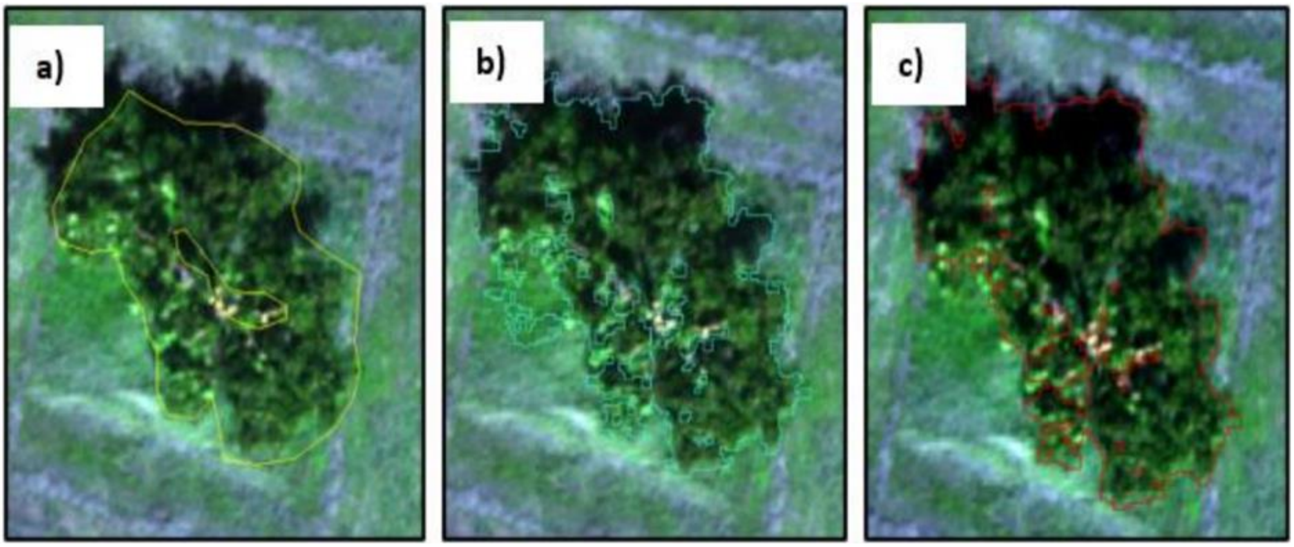


Fig. 10. Crown delineation of tree ID 954 (a) Manual digitize (b) Local extrema algorithm (c) Watershed algorithm

5.5.1 Accuracy assessment for the watershed algorithm

Two techniques were employed to assess the accuracy of the segmentation: the 1:1 technique and the goodness of fit technique. The 1:1 technique involved overlaying the manually digitized layer with the watershed algorithm layer and visually examining the alignment of tree crowns to determine the degree of concordance. Using the 1:1 technique, the segmentation achieved an overall accuracy of 83.3%, with 50 out of 60 trees exhibiting a satisfactory overlay between the manual digitizing and watershed algorithm layers. With regard to the goodness of fit technique, the segmentation attained a total accuracy of 73%, indicating a segmentation error rate of 27%. The over-segmentation measure was found to be 0.220 m^2, while the under-segmentation measure amounted to 0.307 m^2. The result of the accuracy assessment is shown in Table 3.

Table 3
Accuracy assessment of watershed algorithm

Table Head	Accuracy Assessment				
	Total Reference Polygon	Total 1:1 match	Over segmentation	Under segmentation	Distance Index
1:1	60	50			
Goodness of fit			0.220	0.307	0.27
Total Accuracy		83.3%			73%

5.5.2 Accuracy assessment for the local extrema algorithm

The total accuracy of segmentation using the 1:1 technique is 81.7% where 49 trees from 60 trees overlay nicely. In the goodness fit technique, the total accuracy of segmentation is 71% and the error of segmentation is 29% where the over-segmentation is 0.266 m^2 and under-segmentation is 0.307 m^2. Table 4 below indicates the accuracy assessment of the Local Extrema Algorithm.

Table 4
Accuracy assessment of the local extrema algorithm

Head Table	Accuracy Assessment				
	Total Reference Polygon	Total 1:1 match	Over segmentation	Under segmentation	Distance Index
1:1	60	49			
Goodness of fit			0.226	0.307	0.29
Total Accuracy		81.7%			71%

The accuracy assessment results indicate that the watershed algorithm outperforms the local extrema algorithm in terms of accuracy. Using the 1:1 technique, the watershed algorithm achieved a higher accuracy with 50 trees exhibiting a perfect overlay as shown in Figure 11 (a), whereas the local extrema algorithm had 49 trees with a one-tree difference. In terms of the goodness of fit technique, the watershed algorithm demonstrated a lower over-segmentation measure of 0.220 m^2 compared to the local extrema algorithm, which had an over-segmentation measure of 0.266 m^2, resulting in a difference of 0.046 m^2. This discrepancy can be attributed to the misclassification of grass as a tree crown, as depicted in Figure 11 (b), where the manually digitized segmentation is smaller than the segmentation performed by the algorithms. Both algorithms exhibited the same under-segmentation value of 0.307 m^2, as depicted in Figure 11 (c), where the segmentation performed by both algorithms is smaller than the manually digitized segmentation. Overall, the goodness of fit technique revealed that the watershed algorithm achieved a higher total accuracy of 73% compared to the local extrema algorithm, which obtained an accuracy of 71%. This suggests that the watershed algorithm exhibits superior accuracy compared to the local extrema algorithm, whether assessed using the 1:1 technique or the goodness of fit technique.

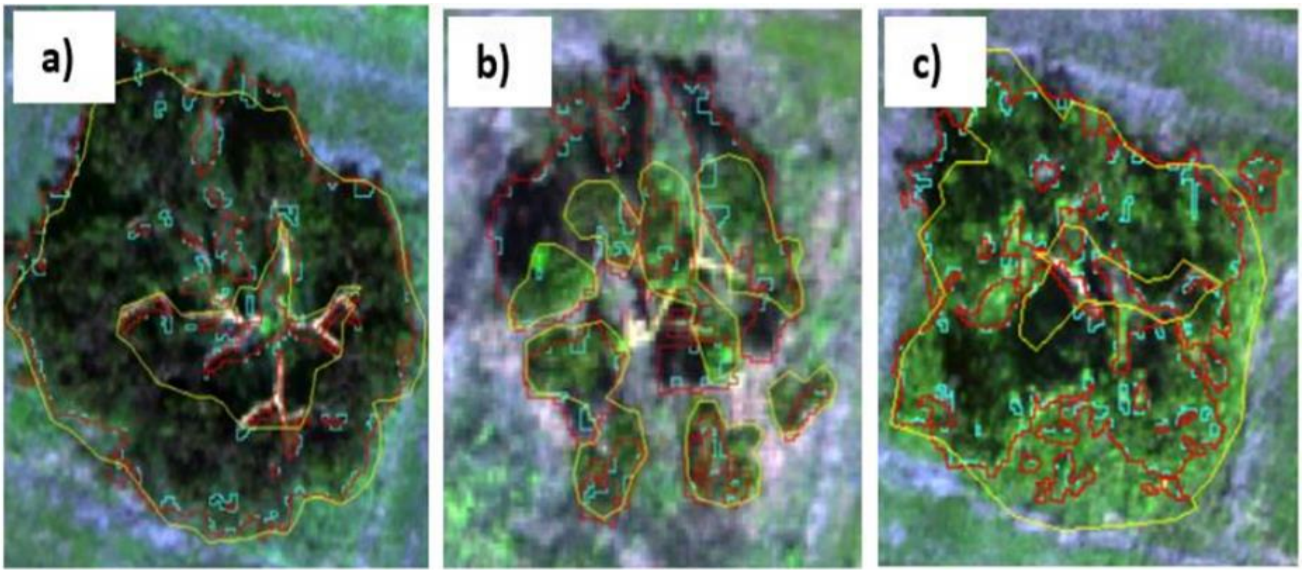
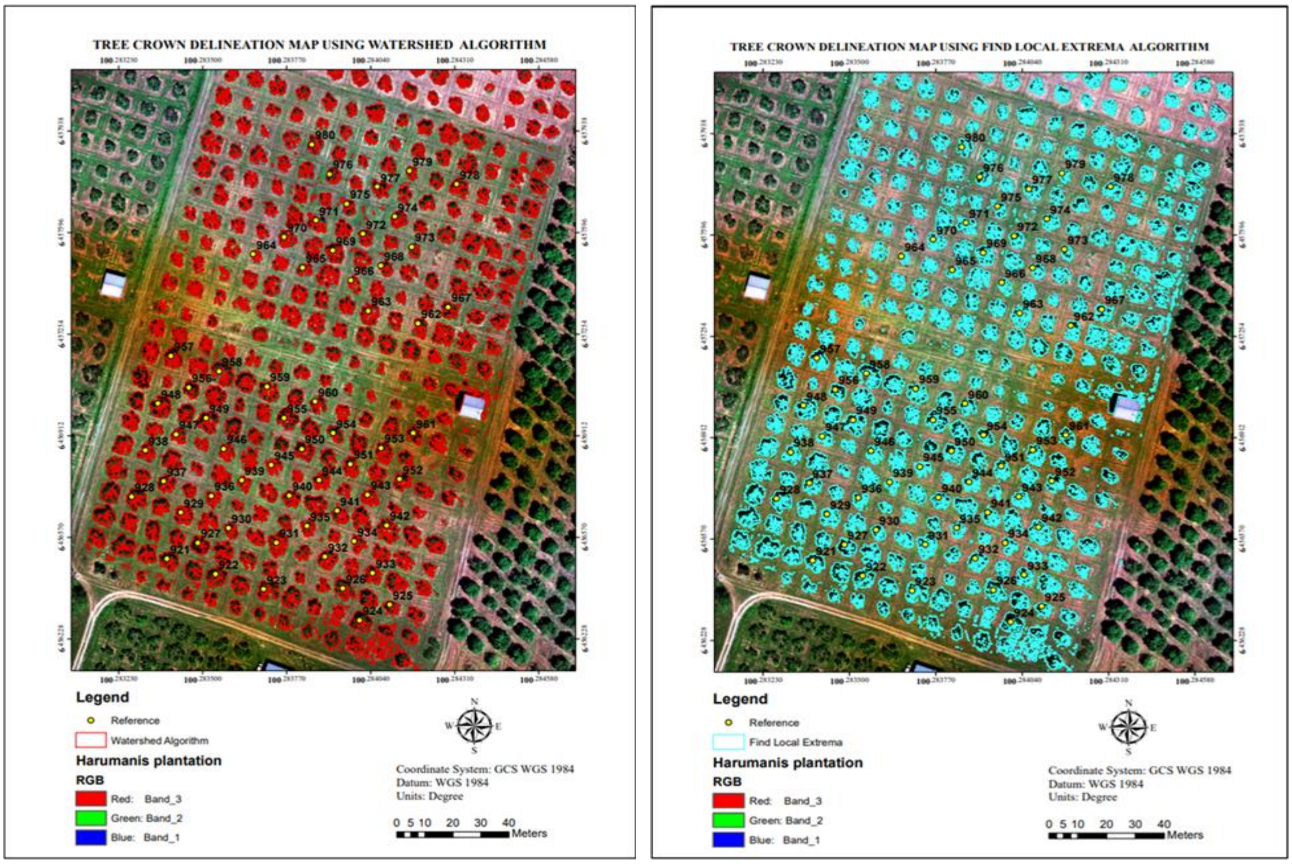


Fig. 11. Manually segmented tree crown delineation in the yellow line, watershed segmented output in the red line while Local Extrema segmentation output in the cyan line (a) Perfect match tree crown (b) Over-segmentation (c) Under-segmentation

5.6 Tree Crown Delineation Map

Figure 12(a) presents the generated tree crown delineation map utilizing the watershed algorithm, which is one of the employed OBIA techniques. The delineated tree crowns are represented by red lines. However, certain discrepancies exist within the tree crown delineation, as the algorithm erroneously identified certain areas of grass and shadow as part of the tree crown. To assess the accuracy of the delineation, the crown projection area (CPA) was computed for each tree crown using ArcMap software. The CPA values will be utilized in the accuracy assessment process to determine the algorithm’s overall accuracy performance.

Figure 12(b) displays the finalized output of the tree crown delineation map obtained using the Local Extrema algorithm. Similar to the map generated through the watershed algorithm, the tree crown delineation is represented by the red lines. The positional markers assigned to each tree serve to indicate their respective IDs. Given that the map encompasses the tree crown delineation of unselected trees in the vicinity, the tree positions aid in identifying the trees that were chosen for analysis. Furthermore, the classification of grass and shadow as tree crowns within the local extrema algorithm results in classification inconsistencies. It is essential to calculate the CPA for the local extrema algorithm as well, which will be utilized in an accuracy assessment to determine the algorithm's overall accuracy performance.



(a) (b)

Fig. 12. Tree crown delineation map using (a) watershed algorithm (b) local extrema algorithm

6. Conclusions

In summary, the comparative analysis between the watershed algorithm and the local maxima and minima algorithms reveals that the watershed algorithm exhibits a higher degree of accuracy. Both algorithms exhibit misclassifications, encompassing shadow, grass, and bare soil being incorrectly classified as tree crowns. However, the local maxima and minima algorithms demonstrate a greater extent of mismatched classifications, resulting in an accuracy assessment of 81.7% using the 1:1 technique and 71% using the goodness of fit technique. Conversely, the watershed algorithm attains an accuracy assessment of 83.3% using the 1:1 technique and 73% using the goodness of fit technique. Furthermore, the local maxima and minima algorithm showcases a higher prevalence of hollow areas being erroneously classified as tree crowns, despite its designation as an advanced classification technique. The goodness of fit technique exposes an over-segmentation value of 0.266 m^2 for the local maxima and minima algorithm, in contrast to 0.220 m^2 for the watershed algorithm, signifying a disparity of 0.046 m^2. The under-segmentation value remains consistent between both algorithms at 0.307 m^2. Taken together, these findings indicate that the watershed algorithm surpasses the local maxima and minima algorithms in terms of tree crown delineation accuracy, exhibiting fewer mismatches and a greater concordance with manual digitization.

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