

ACCURACY EVALUATION OF OIL PALM TREE COUNT USING OBIA AT TENERA SUMBER REJEKI FARMERS GROUP PLANTATION, TERANGKEH, KOTABARU, SOUTH KALIMANTAN

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ABSTRACT

Indonesia holds the largest oil palm plantation area in the world, making accurate tree count data essential for plantation management. Conventional field survey methods are limited in time and cost efficiency, making them impractical for large-scale areas. This final project aims to automatically count oil palm trees using the Object Based Image Analysis (OBIA) method, evaluate detection accuracy, and produce a tree distribution map at the Tenera Sumber Rejeki Farmer Group Plantation, Kotabaru Regency, South Kalimantan. Secondary data were obtained from PT Eshan Agro Sentosa, comprising aerial photo processing results and field survey records. Data processing was conducted using eCognition Developer and QGIS through segmentation and classification stages. Segmentation using the Multiresolution Segmentation algorithm yielded optimal parameters: Scale Parameter (200), Shape (0.3), and Compactness (0.7). Classification was performed using the Nearest Neighbor method with Cluster Random Sampling across five object classes. The OBIA method detected 1,479 oil palm trees within a 10.51-hectare study area, compared to 1,521 trees in the field survey. Accuracy assessment yielded a Detection Percentage (DP) of 93.17% and Branch Factor (BF) of 5.88%, both classified as excellent. Results were visualized in a distribution map integrating OBIA outputs with field survey data.

Keyword : Oil Palm, Object Based Image Analysis, Aerial Photographs, UAV, Tree Counting

1. INTRODUCTION

Indonesia is the country with the largest area of oil palm plantations in the world, accounting for 34.18% of the total global oil palm area (Fauzi et al., 2012). The oil palm (*Elaeis guineensis* Jack) of the Palmae family plays a vital role in Indonesia's economy as a producer of vegetable oil for the industrial sector (Ministry of Agriculture, 2024). Rising consumer demand for vegetable oil has driven the expansion of plantation areas through the planting of a greater number of oil palm trees. Oil palm plantations in Indonesia generally cover vast areas, with a single plantation containing hundreds to thousands of oil palm trees. The vastness of the land and the large number of trees present unique challenges for management and maintenance. The rising demand for palm oil in Indonesia necessitates development efforts in the oil palm sector (Indarti, 2016). This development still faces various obstacles, such as technological limitations, a lack of accurate data on the number of oil palm trees in the field, and inefficient working methods. One of the main challenges that remains is the use of field survey methods to count the number of trees on

large-scale plantations, which is time-consuming and costly (Yana Armanto et al., 2024). The actual population of oil palm trees in the field often differs from estimates due to uneven planting distances and the presence of dead or damaged trees, making data on tree counts obtained through field surveys prone to inaccuracies (Fauzi Garin Setiyawan et al., 2023). These conditions highlight the need for automation and the use of technology to calculate the number of oil palm trees quickly and accurately.

Aerial mapping is a technology that can be utilized for managing the counting of oil palm trees. Aerial imagery data can be used to detect oil palm objects with high resolution and accurate results (Yogi et al., 2020). To support the significant potential of oil palm plantations, the identification of oil palm land, non-oil palm land, and oil palm trees can be performed using the Object-Based Image Analysis (OBIA) method. The OBIA method is a valuable tool for supporting the automation of oil palm plantation management due to its ability to count the number of oil palm trees. Unlike manual methods, which require significant time and labor and carry a high risk of calculation errors, the OBIA method

offers high accuracy, particularly on large-scale land areas (Blaschke et al., 2011).

Various studies have been conducted to address the limitations of field survey methods in counting oil palm trees. The use of high-resolution aerial imagery from Unmanned Aerial Vehicles (UAVs), processed using the OBIA method, has proven capable of automatically detecting oil palm trees with high accuracy. Patricia (2017) achieved an accuracy of 98.50% in counting oil palm trees using the OBIA method in Sintang Regency. Al-Faqih (2020) applied the OBIA method with the Multiresolution Segmentation algorithm and Nearest Neighbor classification in Sintang Regency, identifying 1,375 trees out of 1,658 trees identified through visual interpretation. Caeli (2016) compared manual and OBIA methods in Tanah Laut Regency and demonstrated the efficiency of OBIA in automated counting. Abyanta et al. (2024) combined the OBIA method with Random Forest Machine Learning in Kotawaringin Timur Regency, with a deviation of only 64 trees from 3,034 reference trees. Fadhillah (2024) used deep learning methods to evaluate the accuracy of oil palm tree counting and obtained an average Detection Percentage (DP) of 93.625% in regular planting patterns.

Various studies have demonstrated the advantages of the OBIA method, but several gaps remain to be addressed. Accuracy testing in OBIA-based studies is often benchmarked against visual interpretation rather than field survey data, which better reflects actual conditions in the field. The selection of optimal segmentation parameters in the Multiresolution Segmentation algorithm also still depends on the characteristics of the plantation being studied (Drăguț et al., 2014); this study addresses that gap by adjusting and determining suitable segmentation parameters for the specific characteristics of the smallholder oil palm plantation under study, rather than proposing generalizable parameter recommendations. OBIA has been widely applied for oil palm tree detection and counting, but studies that integrate OBIA-based segmentation and classification workflows in eCognition Developer with QGIS for accuracy evaluation at the smallholder plantation scale, such as the Tenera Sumber Rejeki Farmers' Group Plantation in Terangkeh Village, Kotabaru Regency, South Kalimantan, remain limited. This study contributes a replicable methodological workflow for automated oil palm tree counting that can be applied to similar smallholder plantation conditions.

This study responds to this gap by evaluating an OBIA-based workflow using eCognition Developer and QGIS to support automated oil palm tree counting at the smallholder plantation scale. This

study aims to automatically count the number of oil palm trees using the Object-Based Image Analysis (OBIA) method, calculate the accuracy of the detection results against field survey data, and create a map of the distribution of oil palm trees in the Tenera Sumber Rejeki Farmers' Group Plantation, Terangkeh Village, West Pulau Laut Subdistrict, Kotabaru Regency, South Kalimantan Province.

2. DATA AND METHODS

2.1 Data

The data used in this study are secondary data obtained from PT Eshan Agro Sentosa, consisting of processed aerial photo data and field survey data. Field survey data were collected in shapefile (SHP) format using a Garmin 64s handheld GPS with a positional accuracy of 1–5 meters, conducted from May 6 to June 6, 2024. These data were used as validation data to compare automatic detection results with field survey results.

Aerial photo data were acquired in GeoTIFF format using a WingtraOne VTOL UAV equipped with a Sony RX1R II camera (42 MP), flown at an altitude of 300 m with a ground sampling distance (GSD) of 4.0 cm/px. Data acquisition consisted of 3 flights producing 1,138 photos in total, carried out on May 6, 2024, between 7:00 AM and 3:00 PM under clear weather conditions with wind speeds below 7 m/s. The camera was set at a 90-degree (nadir) angle, with forward and side overlaps of 70–80%. The orthomosaic was processed on May 13, 2024, using Agisoft Metashape, referenced to the UTM Zone 50S, WGS 1984 coordinate system. No ground control points (GCP) or check points (CP) were used in the orthomosaic processing; consequently, the georeferencing accuracy (RMSE) of the resulting orthophoto was not quantified in this study. These aerial photo data served as the primary input for the OBIA method to automatically count oil palm trees.

2.2 Study Area

The oil palm plantation is located in Terangkeh Village, West Pulau Laut Subdistrict, Kotabaru Regency, South Kalimantan Province, as shown in Figure 1. Geographically, the location lies between 116° 05' – 116° 20' E and 3° 20' – 3° 45' S. This area was selected as the final project site because it features an oil palm plantation with a representative land area and available aerial imagery, thereby supporting the application of the OBIA method for automatically calculating the number of oil palm trees. The project area focuses on a single representative block of the oil palm plantation that reflects typical plantation conditions. The final project location is shown Figure 1.

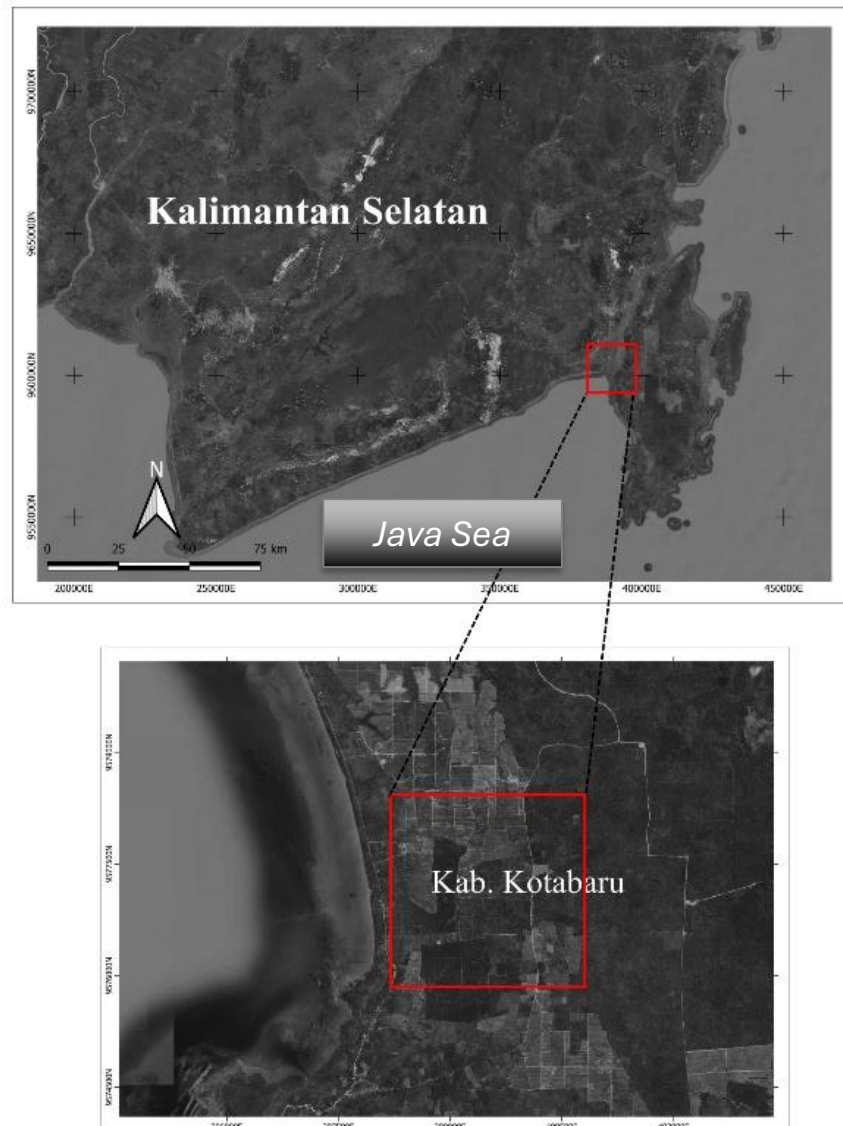


Figure 1. Study Area Location

2.3 Methods

This study employs the Object Based Image Analysis (OBIA) method due to its ability to simultaneously segment and classify objects based on spectral, spatial, and textural characteristics. This method is superior to pixel-based methods in analyzing high-resolution imagery because it can generate segments that correspond to the actual shapes of objects in the field (Blaschke et al., 2014). Data processing was performed using eCognition Developer and QGIS software. The research process consisted of three main stages: the preparation stage, the data processing and analysis stage, and the final stage.

The preparation stage consisted of a literature review followed by data collection. In the data processing and analysis stage, the aerial photo data and field survey data were processed through two parallel workflows. The aerial photo data workflow began with area identification and cropping to the study area boundary, followed by rule set creation in eCognition Developer, segmentation, automatic detection, and OBIA-based tree count calculation, producing a tree density map using the OBIA method. In parallel, the field survey data were cropped to the same study area boundary, after which the distribution and number of trees were calculated to produce a tree distribution map using the field survey method. The results from both

workflows were then compared through an accuracy test against the target thresholds of $DP \geq 80\%$ and $BF \leq 20\%$; if the target was not met, the process returned to the segmentation step for parameter

adjustment. Once the target accuracy was achieved, the results proceeded to result analysis in the final stage, followed by report preparation, as shown in Figure 2.

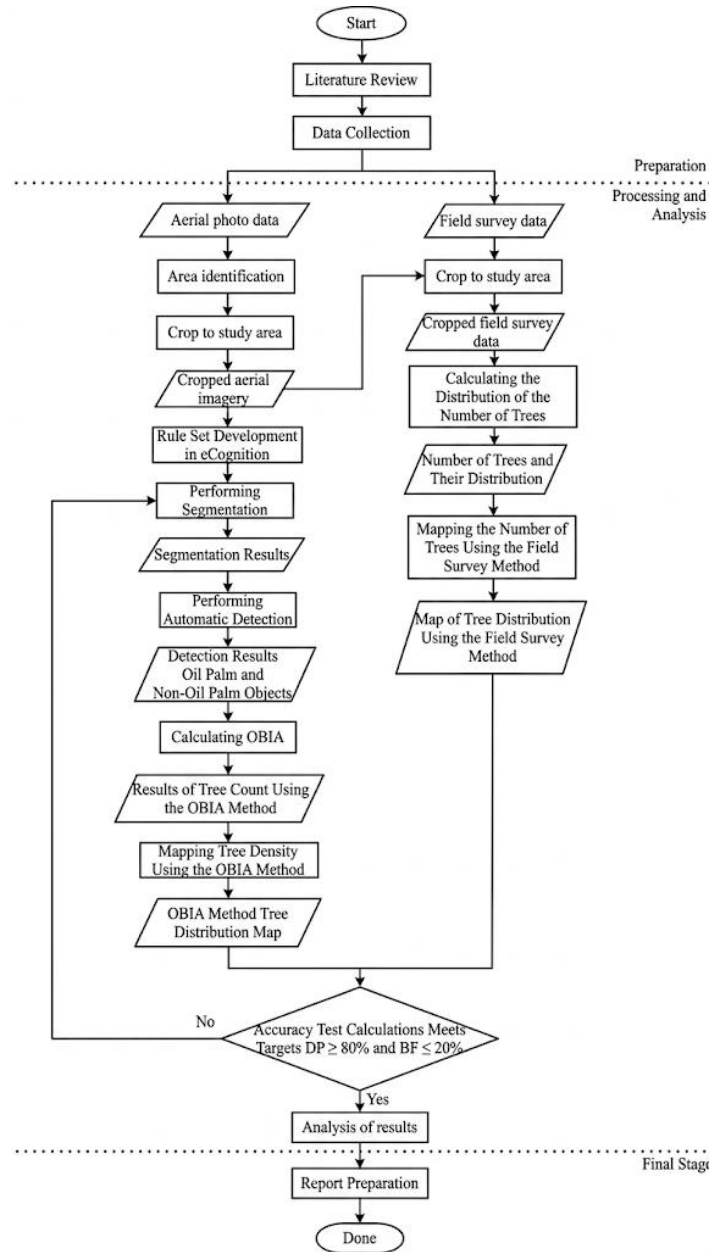


Figure 2. Final Project Flowchart

2.4 Preparation

The initial phase includes a literature review and data collection. The literature review was conducted by gathering references from books, scientific journals, articles, and theses that discuss Object-Based Image Analysis methods. Data was obtained from PT Eshan Agro Sentosa, consisting of aerial

imagery captured using a WingtraOne VTOL UAV on May 6, 2024, and processed using Agisoft Metashape, as well as field survey data collected from May 6 to June 6, 2024. The aerial photo data served as the primary input for the segmentation and detection of oil palm trees, while the field survey data was used as reference data in testing the accuracy of the detection results.

2.5 Data Processing and Analysis Stage

The data processing stage began with the input of two main types of data into the eCognition Developer software: aerial imagery and field survey data. Area identification was conducted to determine a representative study area based on three parameters: tree density, plantation condition, and block area. Block 1 was selected as the study area, covering 10.51 hectares. Cropping of the aerial imagery and field survey data was performed using QGIS to limit the processing area to the boundaries of the selected block. The segmentation stage was conducted using the Multiresolution Segmentation algorithm through two stages: determining the optimal Scale Parameter and optimizing the Shape and Compactness parameters, as these are the three core parameters governing object formation in Multiresolution Segmentation. Parameter selection was carried out through a random trial approach, in which each combination was visually evaluated by comparing the resulting segment boundaries against the actual boundaries of oil palm tree crowns. The first stage tested six Scale Parameter values ranging from 50 to 300, identifying Scale Parameter 200 as the value producing a tree count closest to the field survey data. The second stage tested nine combinations of Shape and Compactness at Scale Parameter 200, based on an inverse relationship between the two parameters. The best parameter combination obtained was Scale Parameter 200, Shape 0.3, and Compactness 0.7, with a discrepancy of 42 trees compared to the field survey data. The classification stage was performed using the Nearest Neighbor method with 995 samples across five object classes. The classification results were exported in shapefile format and converted into centroid points to automatically calculate the number of trees. Accuracy testing was performed by comparing the OBIA detection results against field survey data using the Detection Percentage (DP) and Branch Factor (BF) parameters.

2.6 Final Stage

The final stage is the concluding phase of the entire final project. The final project report is prepared to document the entire process, from the initial stage, through data processing and analysis, to the presentation of information in the form of thematic maps.

3. RESULTS AND DISCUSSION

3.1 Aerial Photo Cropping Results

The acquired aerial photo data was then cropped to define a more specific study area for the tree count calculation process. Aerial photo cropping was performed using QGIS software with existing data. The study area was determined by selecting several

blocks based on observations of key parameters. The observation parameters used in selecting the study area were: (1) the density of oil palm trees within a block, (2) the condition of the plantation, and (3) the area of a plantation block. A visual analysis was conducted on several candidate blocks, and Block 1 was selected as the most representative study area. Block 1 covers an area of 10.51 hectares with a total of 1,521 trees. The characteristics of Block 1 are capable of representing the general conditions of the plantation as a whole. The selection of this single block aims to allow for a more in-depth and focused calculation of the number of trees. The results of the aerial photo data extraction are shown in Figure 3.



Figure 3. Aerial Photo of Block 1

3.2 Segmentation Results

The segmentation process was performed using the Multiresolution Segmentation algorithm in the eCognition Developer software. This algorithm enables the creation of polygons based on pixel value uniformity by adjusting several key parameters: Scale Parameter, Shape, and Compactness. A small Scale Parameter value produces small, detailed polygons, while a larger value produces larger polygons.

The segmentation parameter values were determined using a random trial approach, which involves randomly selecting parameter combinations based on the quality of the resulting segmentation. Table 2 shows six selected trials representing variations in the Scale, Shape, and Compactness parameters. The differences in Table 2 were calculated using the absolute values of the discrepancies between the number of trees detected and the field survey data of 1,521 trees.

Table 1. Variations in Parameter Values in the Segmentation Experiment

Scale Parameter	Shape	Compactness	Tree Count	Difference (Absolute)
50	0.1	0.1	41,287	39,766
100	0.2	0.2	10,436	8,915
150	0.3	0.3	4,784	3,263
200	0.4	0.4	1,779	258
250	0.5	0.5	977	544
300	0.6	0.6	322	1,199

Table 2 shows that the Scale Parameter value significantly affects the number of oil palm trees generated. Values that are too small, such as in the experiment with a Scale Parameter of 50, result in a very large number of trees due to over-segmentation, where a single tree is split into multiple polygons. As the Scale Parameter value increases (100–150), the number of trees decreases but still exhibits excessive segmentation. The results begin to approach field conditions at a Scale Parameter of 200 with a smaller discrepancy. However, at higher values (250–300), the number of trees decreases significantly again due to under-segmentation, where several trees are combined into a single polygon. The differences in segmentation results from each experiment can be seen in Table 3.

Table 2. Variations in the Shape and Compactness Parameters at a Scale of 200

Scale Parameter	Shape	Compactness	Tree Count	Difference (Absolute)
200	0.1	0.9	1,823	302
200	0.2	0.8	1,749	273
200	0.3	0.7	1,479	42
200	0.4	0.6	1,670	149
200	0.5	0.5	1,783	262
200	0.6	0.4	1,354	167
200	0.7	0.3	1,024	497
200	0.8	0.2	770	751
200	0.9	0.1	600	921

Table 3 shows that the optimal parameter combination was obtained in the third experiment, with a Scale Parameter of 200, a Shape of 0.3, and a Compactness of 0.7. This experiment yielded 1,479 trees, a difference of 42 trees compared to the field survey data, which recorded 1,521 trees. A high Compactness value encourages the algorithm to form tighter, circular polygons, so that a single polygon tends to represent only one oil palm tree. The relatively round and regular shape of oil palm tree crowns makes this parameter combination the most optimal compared to the other experiments. This very small difference indicates that this parameter combination is capable of producing segmentation that closely approximates actual field conditions.

3.3 Classification Results

Classification is the next step following the segmentation process, aiming to group the segmented objects into specific classes based on their spectral, textural, and shape/geometric characteristics. This final project performed classification using the Nearest Neighbor method,

where the class assignment for each polygon is based on the similarity of its feature values to those of the training samples. The features used in the classification process included spectral attributes (e.g., mean and standard deviation of pixel values per band), textural attributes derived from the Gray-Level Co-occurrence Matrix (GLCM), and shape/geometric attributes (e.g., area, roundness, and shape index). The object classes used in the classification process for this final project consist of five classes: oil palm, other vegetation, soil, shadow, and water.

Sampling for each object class was performed using the Cluster Random Sampling method, which involves randomly selecting samples based on the class to be chosen. Uniform sampling across the entire area is crucial to ensure that the classification model can recognize object variations in every section. Sampling for the oil palm tree class was conducted by selecting polygons that fully encompass the canopy of the oil palm tree. Most of the polygons used as samples only cover the central portion to avoid contamination by the shadow and ground classes. This method ensures that the values from the oil palm tree samples accurately represent the objects as they appear in the field. A detailed illustration of the oil palm tree sampling process can be seen in Figure 4. The figure shows that the green color represents the oil palm class.

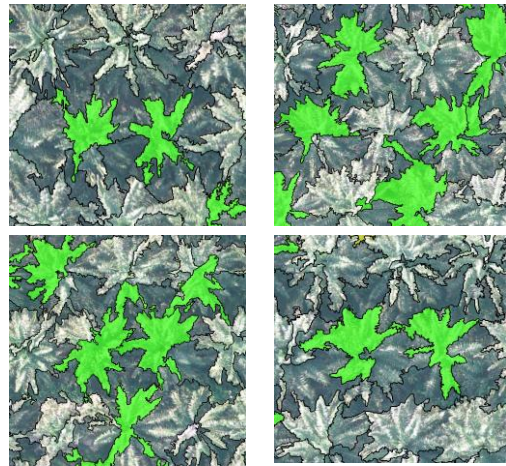


Figure 4. Sampling of Oil Palm Trees

The sampling process was carried out on the segmentation results using the best parameters (Scale Parameter 200, Shape 0.3, and Compactness 0.7). Samples were selected manually by choosing representative polygons for each class across the project area. Samples were distributed throughout the area to ensure the method could recognize variations in object characteristics across different parts of the site. A total of 995 samples were used in the classification process, distributed across the five classes as follows: 711 samples for the oil palm

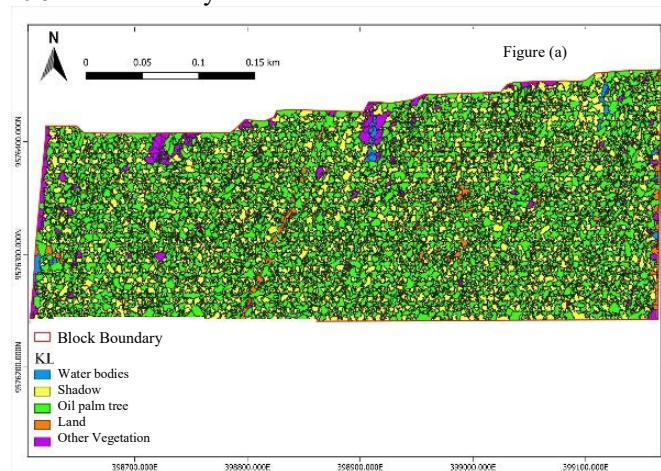
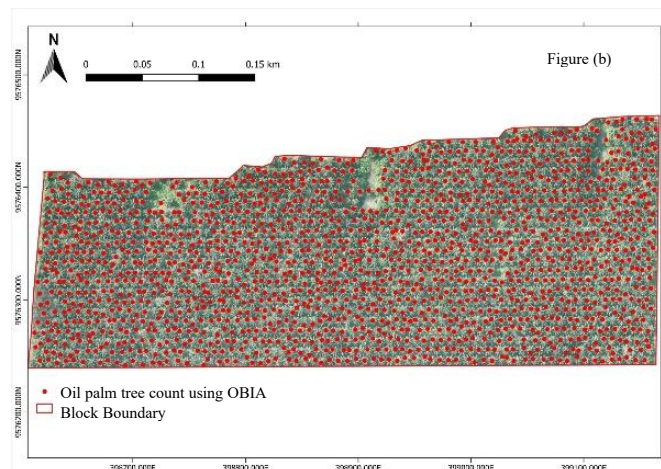
class, 186 samples for the shadow class, 52 samples for the other vegetation class, 32 samples for the soil class, and 14 samples for the water class. Once sampling was complete, it served as the basis for the eCognition Developer software to perform automatic classification, with a processing time of 6 hours. This process classified all segmented objects into the five classes. A visualization of the classification results can be seen in Figure 5(a), which shows the distribution of each object class across the project area.

3.4 Distribution of Oil Palm Tree Counts

The oil palm tree count was carried out on an oil palm plantation in Terangkeh Village, West Pulau Laut District, Kotabaru Regency, South Kalimantan. The tree counting process in this final project used aerial photographs captured by UAV. The OBIA-based tree count was performed by converting the centroid of each polygon classified as oil palm into a point, with each point representing one oil palm tree. The OBIA method detected 1,479 oil palm trees within a 10.51-hectare study area. The

distribution of detected trees is shown using red point symbols in Figure 5(b). The results indicate that several trees were not correctly detected, caused by the similarity in color and texture between oil palm trees and non-oil palm objects, the close spacing between trees making tree boundaries difficult to distinguish, and inaccuracies in sampling during the classification stage.

Field surveying was carried out using a handheld GPS unit, recording the position of each oil palm tree directly in the field. The field survey identified 1,521 oil palm trees within the study area, visualized using yellow point symbols in Figure 5(c). The field survey data reflects the actual number of trees on the ground and was therefore used as the ground truth reference in the accuracy assessment process. Compared to the OBIA method, the field survey produced more accurate tree position data because recording was done directly in the field; however, it required considerably more time and effort, especially for large-scale plantation areas.



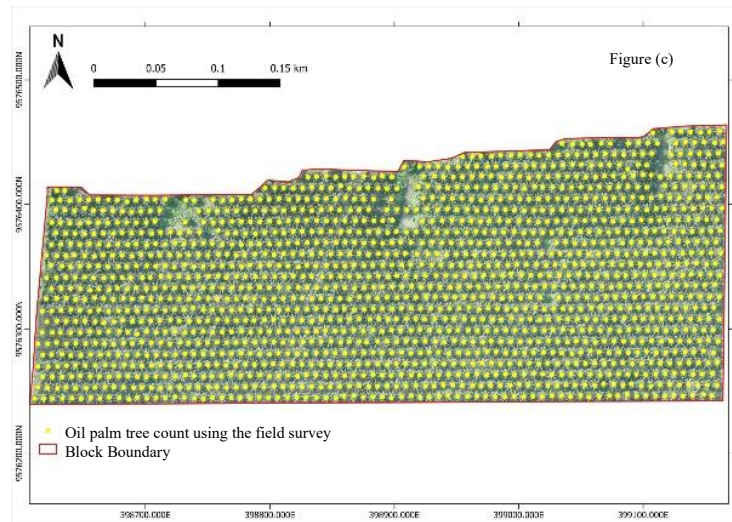


Figure 5. (a) Classification results; (b) Distribution map of oil palm tree count using the Object Based Image Analysis (OBIA) method; (c) Distribution map of oil palm tree count using the field survey method.

3.5 Accuracy Calculation Results

Accuracy testing was conducted by comparing the results of oil palm tree count calculations using the Object-Based Image Analysis (OBIA) method with ground truth data from field surveys. Field survey data was used as a reference because it reflects the actual number of oil palm trees in the field. The comparison between the OBIA method and field survey data can demonstrate the method's accuracy in counting oil palm trees.

Accuracy testing was conducted by comparing OBIA detection results with field survey data using three evaluation categories. A True Positive (TP) is defined as a tree that was correctly detected by the OBIA method and matches the field survey data. True Negative (TN) is defined as a tree recorded in the field survey but not detected by the OBIA method. False Positive (FP) is defined as an object detected as a tree by the OBIA method but not recorded in the field survey. The verification results are presented in Table 4.

Table 3. Results of the Inspection of Oil Palm Trees

Location	Area (Ha)	Ground Truth	TP	TN	FP
Block 1	10.51	1,521	1,392	102	87

The results of the calculations show a Detection Percentage (DP) of 93.17% and a Branch Factor (BF) of 5.88%, which fall into the “very good”

category according to Lin & Nevatia (1998). The accuracy test results are presented in Table 5.

Table 4. Accuracy Test Results

Location	Ground Truth	Plant Type	DP (%)	BF (%)
Block 1	1,521	Oil Palm	93.17	5.88

Based on the results, the DP value of 93.17% indicates that the OBIA method successfully detected the majority of oil palm trees, exceeding the minimum threshold of 80% for the “very good” category. The BF value of 5.88% is well below the 20% tolerance limit, indicating a very low detection error rate.

3.6 Comparison of the OBIA Method and Field Survey Method

The OBIA method and the field survey method are two approaches that can be used to estimate the number of oil palm trees. Both methods share the same objective: to accurately determine the number of trees using different methodologies. The OBIA method uses automated calculations based on UAV aerial imagery, involving segmentation and classification processes. The field survey method employs manual calculations through direct on-site observations and position recording using handheld GPS devices. A comparison of the two methods is presented in Table 6.

Table 5. Comparison of OBIA and field survey methods

No	Comparison Aspect	OBIA Method	Field Survey Method
1	Data Collection Process	Automated using UAV aerial photos through segmentation and classification	Manual with direct field observation
2	Equipment Required	UAV, computer/laptop, aerial photo data	Handheld GPS, stationery, survey personnel, location map
3	Trees Correctly Detected	1,479 trees	1,521 trees

The accuracy test was conducted by comparing OBIA detection results with field survey data to evaluate the detection accuracy of the OBIA method. The accuracy test results yielded three categories: True Positive (TP), True Negative (TN), and False Positive (FP). Of the total 1,479 trees detected by OBIA, 1,392 were True Positives (TP). A tree was categorized as a TP if the OBIA detection point overlapped by at least 1% with the field survey tree point, whether they were completely

overlapping or only partially overlapping. The high number of TP cases indicates that the OBIA method was able to correctly detect the majority of oil palm trees under plantation conditions in the study area. TP conditions are shown in Figure 6(a).

A total of 87 trees were classified as False Positives (FP)—that is, objects detected as oil palm trees by the OBIA method but not recorded in the field survey data. This FP condition was caused by two main factors. First, over-segmentation caused a single oil palm tree to be divided into several small polygons that only covered the tree's edges or shadow, resulting in their classification as oil palm objects. Second, some OBIA detection points were located near field survey points, but the overlapping area did not reach the minimum tolerance threshold of 1%, causing the OBIA polygon's centroid to fall outside the actual tree area. The experimental results show that the combination of parameters Scale 200, Shape 0.3, and Compactness 0.7 produces a lower number of false positives (FP) compared to other parameter combinations. The FP conditions are shown in Figure 6(b).

A total of 102 trees were classified as True Negatives (TN), meaning trees recorded in the field survey data but not correctly detected by the OBIA method. The TN condition was caused by two factors: trees obscured by shadows from other objects, resulting in characteristics different from those in the training sample; and the limitations of the training sample, which did not cover the full range of oil palm tree conditions in the field. The TN condition is shown in Figure 6(c).

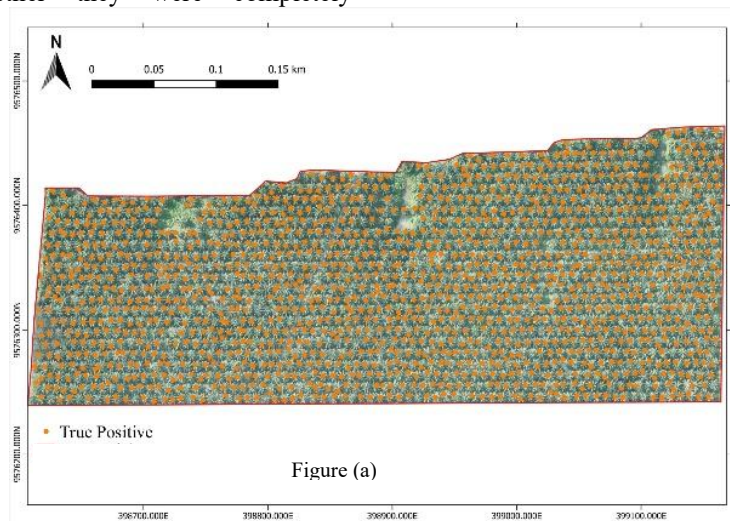


Figure (a)

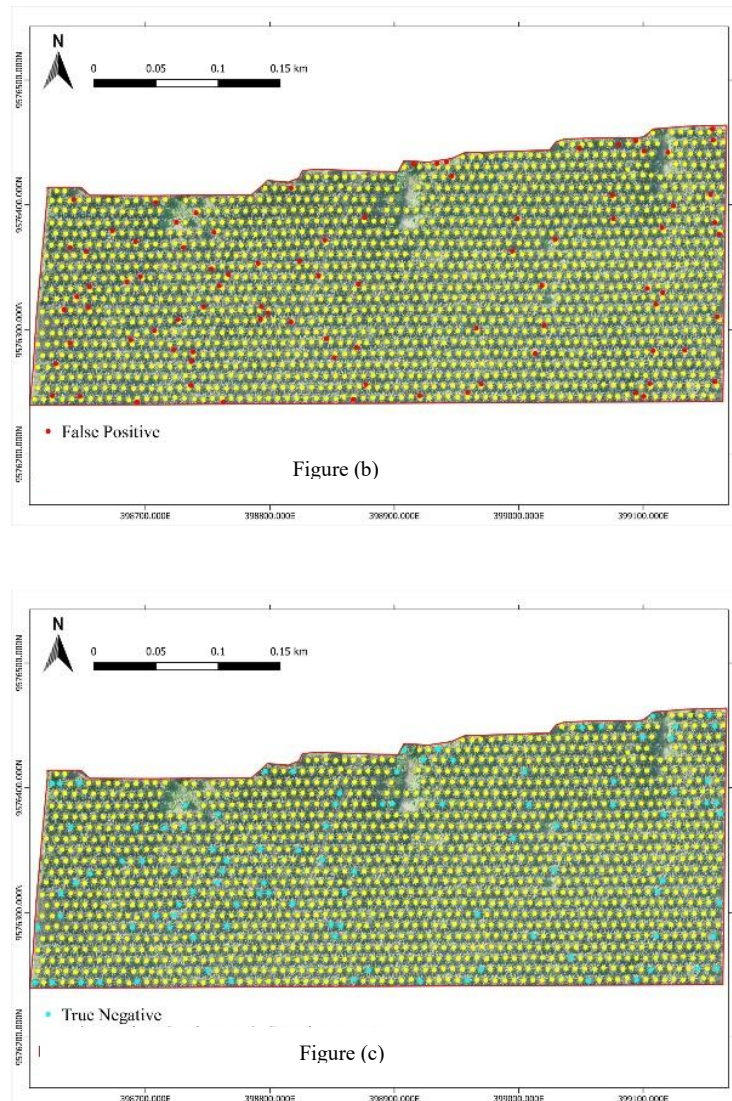


Figure 6. (a) Distribution map of True Positives; (b) Distribution map of False Positives; (c) Distribution map of True Negatives in the automatic detection of oil palm trees.

The difference in point positions between the two methods is due to differences in how the representative points for the trees are determined. The OBIA method determines the position of a tree based on the centroid (geometric center) of the classified polygon representing the oil palm tree. The centroid is determined automatically, with this point representing the center of the oil palm tree as seen in the aerial photograph. The field survey method determines the tree's position based on handheld GPS recordings taken in the field; typically, the operator stands beneath the tree or near the trunk.

3.7 Practical and Academic Benefits of the Research Results

In practical terms, the results of this study are useful for plantation managers, companies, and relevant agencies in quickly obtaining information on the number of trees. This addresses the challenges of plantation management, namely technological limitations, a lack of accurate data on the number of trees, and inefficient field surveys on large tracts of land (Yana Armanto et al., 2024). The OBIA method detected 1,479 trees compared to 1,521 trees in the field survey, with a Detection Percentage (DP) of 93.17%, thereby aiding in updating inventory data, monitoring plantation conditions, and planning maintenance activities. The tree distribution map (Figure 5b) provides a comprehensive overview of

the plantation's condition, allowing managers to identify areas with missing or undetected trees without having to traverse every block. Because it uses UAV aerial imagery and commonly used software (eCognition Developer and QGIS), this workflow can be repeated for each flight to compare tree counts over time, and has the potential to reduce the time and effort required for field surveys. Nevertheless, field surveys remain necessary to validate detection results and improve data reliability. From an academic perspective, this study can serve as a reference for other researchers in developing similar methods for other studies.

3.8 Direction for Future Research

This study opens up opportunities for further development. Future research is recommended to (1) test the workflow on blocks with different planting densities, tree ages, and canopy conditions to assess its applicability under more diverse plantation conditions; (2) add ground control points (GCPs) and check points to measure orthophoto accuracy; (3) utilize canopy height data from a digital surface model (DSM) or multispectral channels to improve the separation of oil palm from other vegetation and shadows; and (4) compare OBIA with deep learning approaches (Li et al., 2017; Mubin et al., 2019). These developments are expected to improve the accuracy and reliability of the results, as well as expand their benefits for oil palm plantation management.

4. CONCLUSIONS AND SUGGESTIONS

This study demonstrates that the Object-Based Image Analysis (OBIA) method, implemented through the integrated workflow of eCognition Developer and QGIS, can automatically count oil palm trees at the smallholder plantation scale with a high level of accuracy, achieving a Detection Percentage of 93.17% and a Branch Factor of 5.88%, classified as "very good" based on the success categories of Lin and Nevatia (1998). These results confirm that the segmentation parameters (Scale Parameter 200, Shape 0.3, Compactness 0.7) determined for this study's specific plantation conditions produced a reliable and replicable counting method, addressing the research objective of evaluating OBIA's applicability at the smallholder scale. Beyond tree counting, the resulting oil palm distribution map provides a practical basis for plantation management and monitoring activities.

Given its relatively fast processing time, this workflow can be applied as a routine monitoring tool for smallholder oil palm plantations,

complementing rather than replacing periodic field surveys, which remain necessary to validate data accuracy over time. Future studies are recommended to test the replicability of this parameter-selection approach across plantations with different tree densities and canopy conditions, in order to assess how generalizable the workflow is beyond the specific case examined here.

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