ISSN 2029-6991 / eISSN 2029-7009

GEODESY and CARTOGRAPHY

2025
Volume 51
Issue 4
Pages 243–254
https://doi.org/10.3846/gac.2025.21974

UDC 528.7

INTEGRATION OF AERIAL PHOTO AND LIDAR DATA FOR DETERMINING THE POSITION AND HEIGHT OF OIL PALM TREES USING OBJECT-BASED ANALYSIS AND CANOPY HEIGHT MODEL ALGORITHM

Lutfi'ah Noviani ROHMAH [1], Naufal SETIAWAN [2]✉, Mochamad Irwan HARIYONO [3], Agung SYETIAWAN [4]

[1,2]Geomatic Engineering, Faculty of Mineral Technology and Energy, Universitas Pembangunan Nasional "Veteran" Yogyakarta, Indonesia
[3,4]National Research and Innovation Agency, Bogor, Indonesia

Article History:
- received 05 August 2024
- accepted 29 November 2025

Abstract. The monitoring of oil palm trees using various technologies, methods, and software is conducted to replace the traditional techniques that are less effective. In this study, an analysis was conducted on the automatic detection results of oil palm trees to determine the estimated height of the trees. The trees were automatically extracted and calculated using eCognition Developer and eCognition Oil Palm Application (OPA) with the Object-Based Image Analysis (OBIA) algorithm on three sample areas: homogeneous, semi-homogeneous, and heterogeneous. The performance test of the two software on the three samples showed that the detection accuracy reached more than 80%. The automatic detection results were used to calculate the tree height using the Canopy Height Model (CHM). The Root Mean Square error (RMSe) was calculated for all centroid samples to evaluate the accuracy of the tree position detection and as a basis for determining the height. The RMSe position result of eCognition OPA was lower than that of eCognition Developer. The RMS values for the homogeneous; semi-homogeneous; and heterogeneous areas were 0.8149; 0.7772; and 0.02118 for eCognition OPA, respectively, which are lower than the values of 0.7718; 0.9044; and 1.0517 for eCognition Developer, this indicates better estimated tree height results.

Keywords: palm oil, aerial photo, LiDAR, tree count, position, tree height.

✉Corresponding author. E-mail: ***naufal.setiawan@upnyk.ac.id***

1. Introduction

Oil palm is one of the plantations commodities that plays a quite important role in the economic activities in Indonesia (Susanti & Maryudi, 2016). Therefore, oil palm commodity ranks third as the largest non-oil and gas foreign exchange contributor to the country after rubber and coffee (Sastrosayono, 2003). Oil palm production in Indonesia from large plantations, private, and community-owned ones have tended to increase along with the expansion of oil palm plantation areas from 2013 to 2017 (Badan Pusat Statistik, 2017). In plantation management, counting and detecting trees is one of the important tasks (Lourenço et al., 2021). Manual field-based counting of oil palm trees requires a lot of labor, is expansive, and time-consuming (Hashim et al., 2020).

Remote sensing and aerial photography can be used as alternatives to provide fast information, efficiently, continuously, consistently, and cover a wide area with cost savings (Held et al., 2003; Purnamasayangsukasih et al., 2016). Remote sensing can be used to monitor oil palm plantation areas because oil palm has distinctive characteristics that are easily recognized (Nurmasari & Wijayanto, 2021). The palm crown looks like a star-shaped canopy when viewed from above.

Detection of oil palm using various methods has been widely conducted, such as the Object-Based Image Analysis (OBIA) method (Rizeei et al., 2018), deep learning methods (Kipli et al., 2023; Putra & Wijayanto, 2023), based on color histogram with supervised classification (Hamdani et al., 2021), and template matching algorithm (Norzaki & Tahar, 2019; Syetiawan & Haidar, 2019).

Additionally, integration of Light and Detection Ranging (LiDAR) and Unmanned Aerial Vehicle (UAV) photogrammetry has been conducted to measure canopy and tree height (Y. Hao et al., 2019; Zhou et al., 2022). LiDAR is an active sensor widely used to determine object distance (Smith et al., 2008) and able to collect high-resolution information about forest structure (Münzinger et al., 2022). With the existence of LiDAR technology, aerial photography (Irsanti et al., 2018), machine learning algorithms, and digital image processing, it is expected to address the existing issues in oil palm plantations, particularly in Indonesia.

Canopy Height Model (CHM) is a surface model that represents vegetation elevation above ground level, reflecting the distance between the Earth's surface and the tree tops (Khosravipour et al., 2015). The CHM usually utilized to estimate forest parameters (J. Hao et al., 2023). Canopy height is a widely used method because it is an important attribute that can be used to obtain other structural characteristics of the forest such as stand volume, basal area, and Above-Ground Biomass (AGB) (Alexander et al., 2018; Wang et al., 2021; Webster et al., 2023). J. Hao et al. (2023) compared tree height extraction between UAV and LiDAR acquisition data. Then, the researches resulted in better tree height extraction with LiDAR.

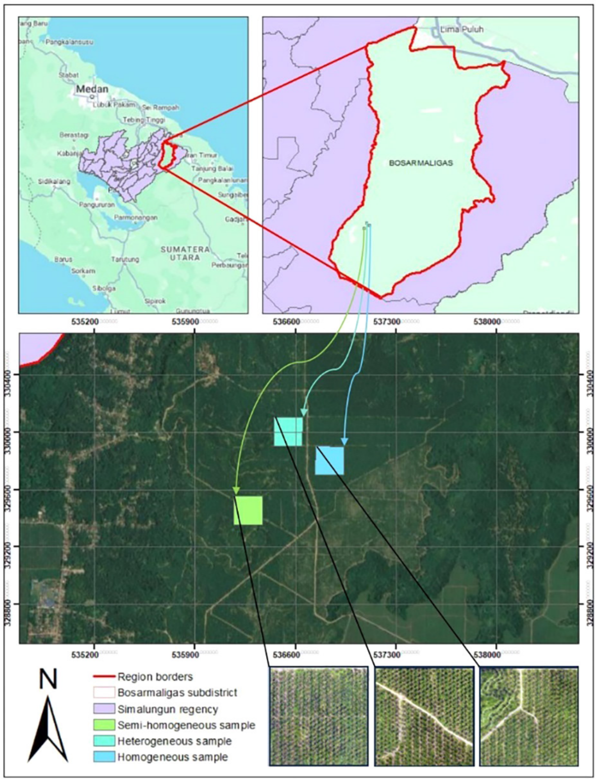


Figure 1. Location map and research samples

In previous research, identification was done separately between tree counting and tree height measurement. In this study, we identify and conduct trees counting automatically using eCognition softwares to observe the accuracy of the extraction points as the basis for estimating tree height. With the positional information of the extracted tree points from high-resolution orthophoto data, tree height can be determined using CHM from Digital Surface Model (DSM) and Digital Terrain Model (DTM) resulting from LiDAR data. Furthermore, we compared the results from eCognition Developer and OPA to show which software is better.

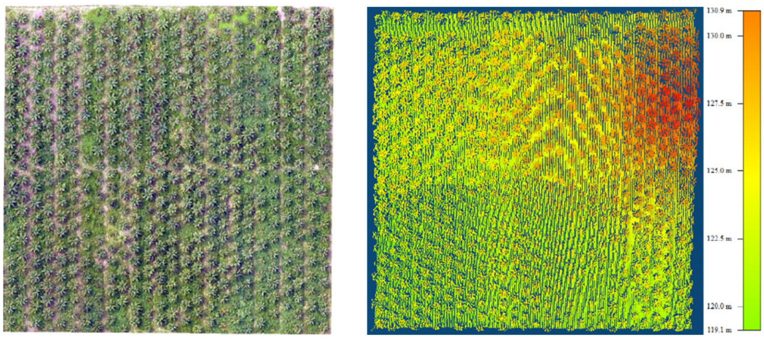
2. The study area

The research location is in Sei Mangkei, Bosar Maligas, North Sumatra (Figure 1). The area used is part of the Sei Mangkei Special Economic Zone (SEZ) oil palm plantation area. The area research covers a total area of 200m x 200m. The selection of the area is due to the fact that it is the first SEZ to be inaugurated in 2015 as the center for the development of large-scale palm oil industry managed by a company. The oil palm plantation is also well-organized, making it easier for the identification process. Additionally, the area provides a mixed area with three types of regions: homogeneous regions, semi-homogeneous regions, and heterogeneous regions.

3. Methodology

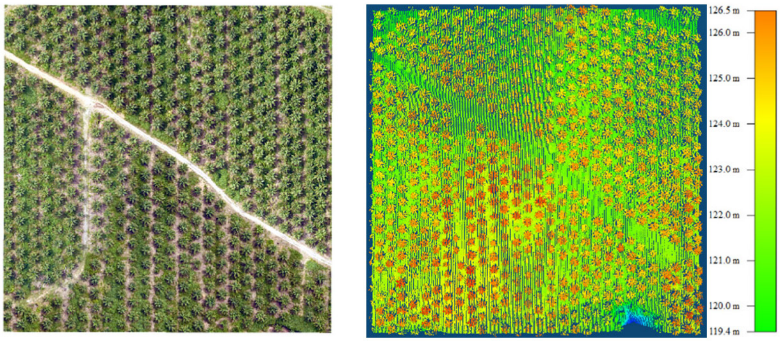
3.1. Data detail

The research was conducted using aerial photo data and LiDAR data acquired simultaneously. Both data sets are secondary data acquired by the Geospatial Information Agency of Indonesia (BIG) in 2016. The aerial photo data used is orthophoto data that has been processed. Aerial photo is a photographic map obtained from aerial surveys by aerial photography in specific areas following certain photogrammetric rules (Priambodo et al., 2022). The main difference between an orthophoto and a map is that an orthophoto forms a photographic image, whereas a map



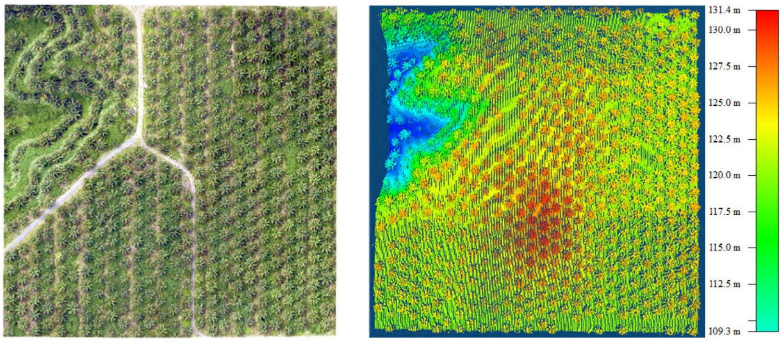
a) b)

Figure 2. Homogeneous sample: a) orthophoto data; b) point cloud LiDAR semi-homogeneous sample



a) b)

Figure 3. Semi-homogeneous sample: a) Orthophoto data; b) Point cloud LiDAR heterogeneous



a) b)

Figure 4. Heterogeneous sample: a) Orthophoto data; b) Point cloud LiDAR

uses lines and symbols depicted according to scale to reflect appearances (Wolf, 1978). Meanwhile, LiDAR point cloud is a set of discrete points in 3D space characterized by Cartesian coordinates stored as tabular data in space-separated value text files (Peynaud & Momo Takoudjou, 2024).

Figures 2–4, show 3 (three) areas used in the research with different oil palm plantation conditions hereinafter referred to as samples. The homogeneous sample consists of a row of well-organized oil palm trees without any other objects within it. The semi-homogeneous sample consists of a row of well-organized oil palm trees with other objects within it, such as roads. The heterogeneous sample consists of a mixed row of oil palm trees that is less organized with other objects within it, such as roads.

3.2. Processing

The strategy of our approach in this study consists of the follow in main steps (can be seen in Figure 5). Firstly, LiDAR Data processing for DTM and DSM creation. Secondly, manual and automatic counting of oil palm trees based on aerial photo data. Thirdly, coordinate extraction for positioning. Fourthly, elevation extraction from DTM and DSM to get CHM. Lastly, is accuracy assessment.

3.2.1. Preparation

A literature study was carried out to find research gaps, solve problems from previous research, and obtain refer-

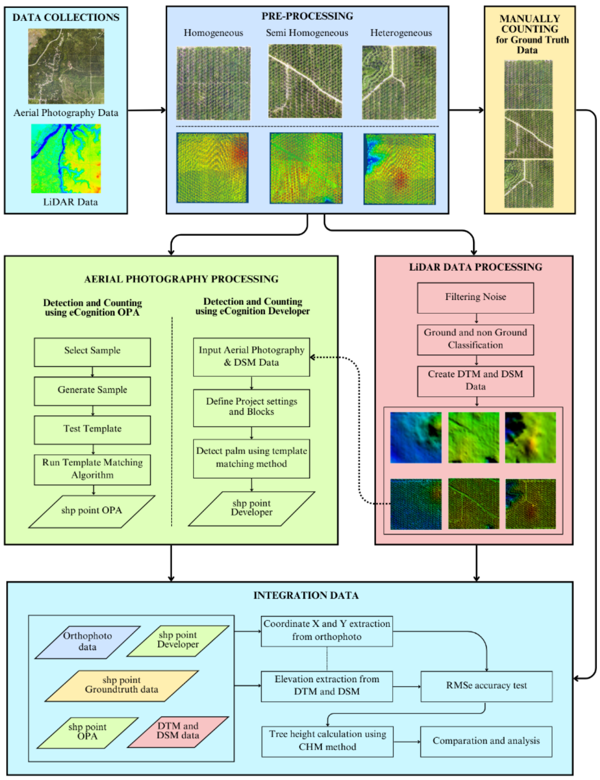


Figure 5. General strategy diagram

ences that support the research. During the preparation stage, software was also installed on the hardware used to support data processing in the study.

3.2.2. LiDAR data processing

Data processing of LiDAR in this research is carried out through three processes despite using two different software. The input data used is LiDAR point cloud data in *.las format, previously cropped and adjusted to the orthophoto data area. Many methods with other software are applied, but most utilize CHM to extract tree height (J. Hao et al., 2023) with 3 stages of point cloud processing.

1. Removing noise that is not integrated with other objects to obtain dense point cloud and DSM;
2. Classifying ground and non-ground points (tree point cloud) to obtain DTM. The process separates points on the ground surface from those outside (Z. Zhang et al., 2018);
3. CHM is obtained by subtracting DSM from DTM.

LiDAR data filtering is carried out to separate or extract specific parts of the point cloud and remove noise. Noise filtering is done manually using the crop feature to select certain parts of the point cloud and remove unnecessary parts. The classes are divided into 2 (two), namely ground and non-ground classes. The ground class is utilized to indicate objects in the form of land or land, while the non-ground class is used to indicate objects above the ground, for instance buildings or plants. In this research, the non-ground object focuses on plant objects, namely oil palm trees. In this process, ground and non-ground classification is carried out automatically using the automatic classification method of the Cloth Simulation Filter (CSF) (Li et al., 2021; W. Zhang et al., 2016).

The point cloud that has been classified then continues to create a DTM and DSM. DTM is created based on the point cloud resulting from ground classification, while DSM is created based on the point cloud resulting from noise filtering. As a result of creating a DTM and DSM, the point clouds become integrated, showing the height of the topographic conditions. To create CHM, the Digital Surface Model (DSM) is normalized using the Digital Terrain Model (DTM) from the desired area, namely DSM – DTM = CHM (Okojie et al., 2020).

3.2.3. Aerial photo processing

Manual calculations to obtain comparative data or ground truth were conducted by manual digitization using ArcGIS software by adding point shapefiles at each canopy point in the aerial photo view. The point shapefile was added precisely at the midpoint of the canopy of each tree. This was done because the assumption is the height of the tree can be determined through the top of the object, which is the midpoint of the oil palm tree canopy.

Processing of orthophotos was done using two software programs, namely eCognition Developer and eCognition OPA (Oil Palm Application). Two software programs used to evaluate the reliability of automatically extracted oil palm trees are designed to provide accurate height estimates

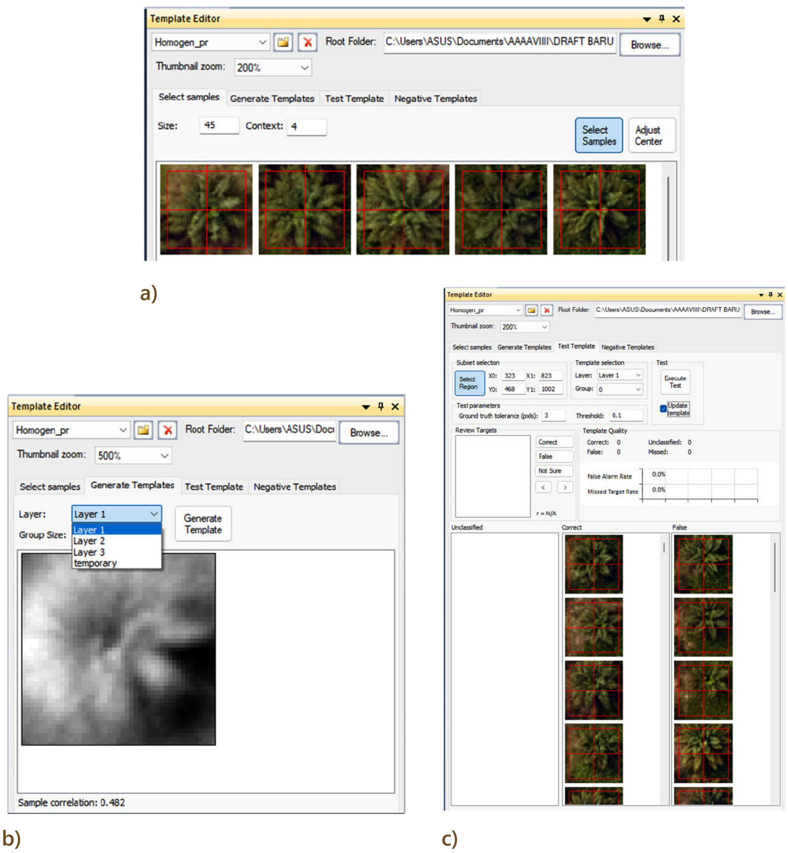


Figure 6. Palm oil tree extraction process with eCognition Developer: a) select sample; b) generate sample; c) test template

based on the Canpy Height Model (CHM) method. Oil palm tree extraction with eCognition Developer software using a template matching algorithm. The template matching algorithm matches each part of the aerial photo data with a previously created template shown in Figure 6.

Select sample is the process of selecting oil palm trees as samples to be used as a reference algorithm for detecting oil palm trees. At this stage, size and context parameters can be set and adjusted to the size of the existing oil palm tree. The size parameter functions are to set the size limit of the object or the size of the shape that includes the tree canopy. Meanwhile, the Context parameter functions for object recognition to help increase accuracy in object detection. The parameter used to detect oil palm trees are Size 45 and Context 4, where these parameters cover the entire canopy of oil palm trees.

Generate template is the process of creating a template or model that is used as a reference in tree detection. Generating templates is done using tree samples that have previously been selected in select samples. Therefore, the shape of the template depends on the tree samples selected. Template testing stage in identifying trees using Test Template. This process involves object recognition where the software will match the object with a template created based on the correlation. Object recognition's accuracy level is influenced by the threshold value used. The existence of a threshold will limit and determine the intensity/value of pixels that are considered part of a particular object, in this case the template that has been created. Threshold is used to separate objects from the background and helps optimize algorithm performance in object recognition. The threshold value ranges from 0 to 1, where using a too-tight threshold (close to 1) can cause objects to be lost, while a too-loose threshold (close to 0) can result in many false detections.

Oil palm tree extraction using eCognition OPA uses a template matching algorithm with more straightforward work steps. Automatic extraction using eCognition OPA software, slightly differs from eCognition Developer with a model that has been provided and trained previously. The workflow is simplified by eliminating the need for several user-defined parameters, shown in Figure 7.

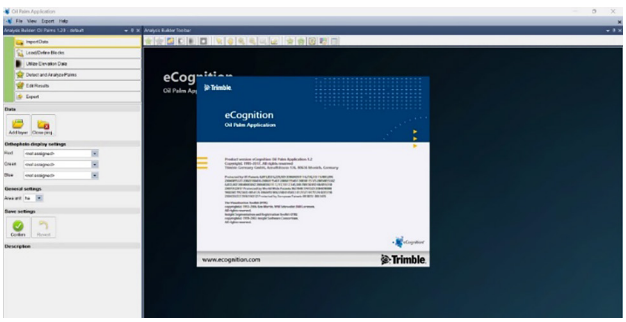


Figure 7. Palm oil tree extraction process with eCognition OPA

Import data is the process of entering orthophoto data in *.tiff format and can be added regarding the DSM of the research area. Define Blocks of defining the desired projection system according to the research area. Detect Palms is the process of automatically detecting objects by software. In this process there is a sensitivity parameter that can be adjusted from 0 to 1. Based on triall and error parameter sensitivity used in the detection of oil palm trees is 0.7, which shows better results than the sensitivity of other parameters. The sensitivity parameter is used to limit and determine the intensity/value of pixels that are considered part of a particular object, in this case the model provided by the software. Automatically saving the original extraction results of oil palm trees without editing with Export Shapefiles.

3.2.4. Test calculation performance with ground truth data

After extracting oil palm trees using both eCognition Developer and eCognition OPA software, the next stage is to test the calculation performance with comparative data. The performance test for calculating the number of oil palm trees resulting from automatic extraction was carried out by comparing it with data from manual calculations, which were considered conditions in the field and used as comparative data.

The results of extracting information on the position and elevation of oil palm trees are used to determine the difference in height resulting from differences in detection points. Accuracy is calculated using a confusion matrix assessment, which is commonly used in assessing machine learning performance, namely precision, recall and F1 score (Nyland, 2016). The confusion matrix compares the predictions made by the model and the actual values from the dataset.

$$Precision = \frac{TP}{TP + FP}; \tag{1}$$

$$Recall = \frac{TP}{TP + FN}; \tag{2}$$

$$F1 - score = \frac{2 \times precision \times recall}{precision \times recall}, \tag{3}$$

where, r (recall) is the tree detection rate, p (precision) is the correctness of the detected trees, F is the overall accuracy of the detected trees, TP (true positive) is the number of correctly detected trees, FN (false negative) is the number of trees that were not detected (omission error), and FP (false positive) is the number of extra trees that did not exist in the field (commission error) (Yun et al., 2021). The performance test for calculating the number of oil palm trees resulting from automatic extraction with eCognition Developer and eCognition OPA was carried out by comparing it with data from manual calculations, which were considered conditions in the field and used as comparative data.

Precision is utilized to measure the precision or accuracy of the model in identifying an object, namely the ratio of true positive predictions compared to the overall data of positive predicted results. Meanwhile, recall is used to measure the accuracy of the model when it succeeds in correctly classifying existing positive examples and compares it with the overall true positive data, in other words, the level of success of the model in finding and remembering objects. F1 score is a single performance measure, an average of combining precision and recall, which provides individual or individual information. The F1 score reflects the balance between precision and recall by providing a more comprehensive picture of the model's performance in classifying positive (correct) and negative (incorrect) examples.

3.2.5. Integration of LiDAR data and aerial photography processing result

Integration was carried out on the shapefile data resulting from the detection and calculation of palm oil and then added with orthophoto data which had X and Y position coordinate information for coordinate extraction. Coordinate extraction is carried out by adding new fields, namely X and Y coordinates, which are then defined via calculate geometry or the add X Y coordinates tools. Subsequently, information regarding the X and Y coordinates will be added automatically. Coordinate extraction is carried out on all data resulting from automatic extraction of oil palm trees as well as comparative data that has previously been created. Figure 8 shows the add XY coordinates tools.

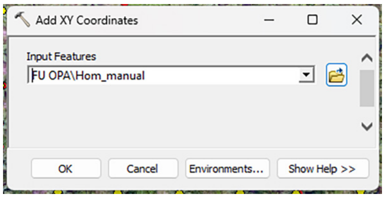


Figure 8. The add XY coordinates window displays

Meanwhile, elevation extraction was carried out on the DTM and DSM data for each shapefile point resulting from the palm oil detection and calculation. The resulting DTM and DSM values are then calculated mathematically by CHM (Canopy Height Model), which is obtained by subtracting the height information from the DSM from the ground surface height from the DTM. Elevation extraction from oil palm tree shapefiles was carried out automatically using the extract multi values to point tool in ArcMap.

Elevation data extraction was carried out from both DTM height data to obtain information on the height of the ground surface and DSM data to obtain information on the height of the tops of oil palm trees. Information extraction is carried out to determine the height of the object above the ground surface. The height value obtained from elevation extraction based on DTM and DSM is the height of the ellipsoid calculated along the normal line of the ellipsoid that passes through a point. The height of the ellipsoid is then denoted by the letter (h). Figure 9 is a display of the elevation extraction process for an oil palm tree shape file.

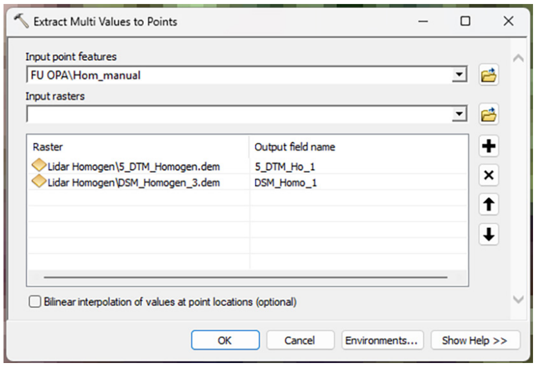


Figure 9. The extract multi values to points window displays

Tree height measurements in this study were carried out using mathematical CHM (Canopy Height Model) calculations obtained by subtracting height information from the DSM from the ground surface height from the DTM. The calculation is carried out by adding a new field of tree height information to the attribute table and then subtracting the DSM-DTM using the field calculator tool in ArcMap. CHM calculations to obtain information on the height of oil palm trees are carried out on all tree extraction results automatically, as well as comparative data that has previously been created. Figure 8 is a display of CHM calculations using the field calculator feature, carried out by subtracting the results of the DSM-DTM elevation extraction in the new field of the attribute table.

The height obtained from the calculation is the height of the ellipsoid denoted by (h). The ellipsoid height of a point is the height of that point above the ellipsoid calculated along the normal line of the ellipsoid that passes through that point (Abidin et al., 2004). Ellipsoid height is the straight-line distance taken along the normal ellipsoid plane from the geometric surface taken from the reference ellipsoid to a certain point where GPS is one of the observation tools that used this height system (Featherstone & Kuhn, 2006).

3.2.6. Comparison and analysis of extraction results

Comparison and analysis are carried out on information resulting from automatic tree extraction against comparative data which is used as a reference and is considered correct. In this study, the accuracy value was calculated from all total samples of correct tree detection results from tree extraction using eCognition Developer and eCognition OPA.

Accuracy tests were carried out to see how much influence the position of the extracted points had on determining tree height estimates. The difference in coordinates and tree height indicates an error. The magnitude of the error is indicated by the RMSE (root mean square error) value (Federal Geographic Data Committee, 1998).

$$RMSe = \sqrt{\frac{actual\,value - predicted\,value)^2}{n}}. \tag{4}$$

4. Result and discussion

4.1. Results of creating DTM and DSM from LiDAR data

LiDAR point cloud data processing is used to obtain DTM and DSM data, which shows altitude values. The height value obtained from elevation extraction based on DTM and DSM is the height of the ellipsoid calculated along the normal line of the ellipsoid that passes through a point. DTM represents the land surface shown in Figure 10 while DSM will represent the land surface and the oil palm trees above it shown in Figure 11. DTM and DSM creation is used to obtain CHM (Crown Height Model) values which represent the height of objects above the earth's surface.

4.2. Results of manual and automatic extraction of oil palm trees

Table 1 shows the results of the manual digitization of oil palm tree calculations as ground truth comparison data. Manual digitization extraction is carried out with visual interpretation based on color, shape and pattern. The oil palm trees that were successfully identified in each sample area were 550 trees in the homogeneous sample, 516 trees in the semi-homogeneous sample, and 503 trees in the heterogeneous sample.

The results of manual digitization are then used as ground truth data to calculate position accuracy as a basis for determining the height of oil palm trees. \The results of extracting oil palm trees using eCognition Developer and eCognition OPA software take less time than calculating oil palm trees using manual digitization. The time required to automatically extract oil palm trees using eCognition Developer and eCognition OPA against manual digitization is shown in Figure 12.

Table 1. Information of ground truth data

Number	Sample	Results
1	Homogeneous	550 oil palm trees
2	Semi-homogeneous	516 oil palm trees
3	Heterogeneous	503 oil palm trees

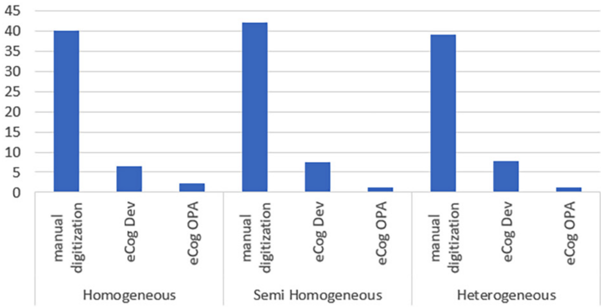
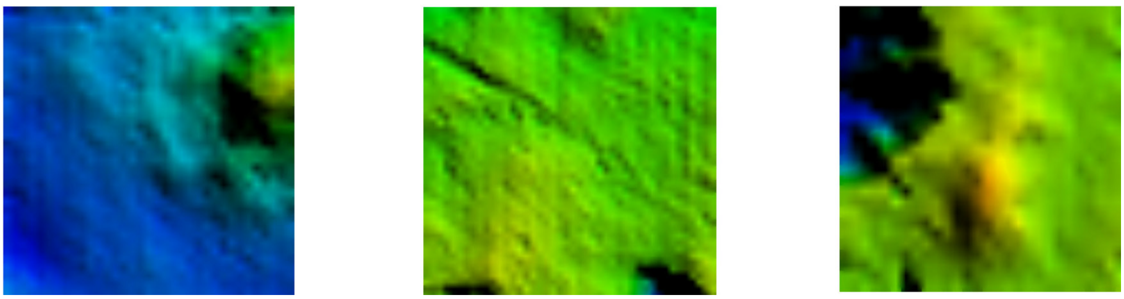


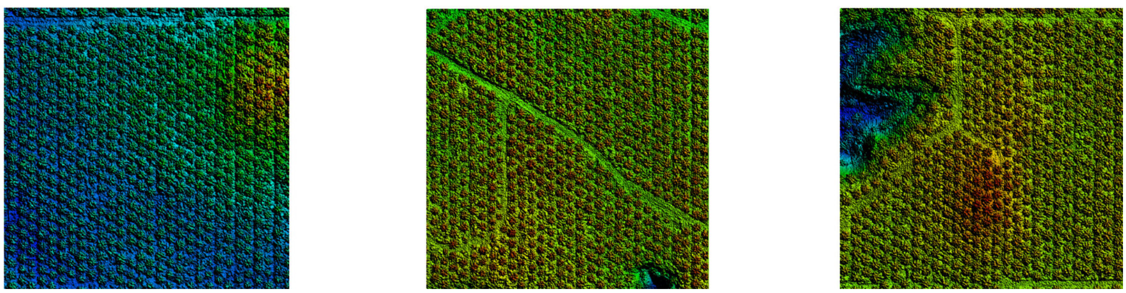
Figure 12. Processing time comparison graph

Nonetheless, the results of extracting oil palm trees automatically using eCognition Developer and eCognition OPA do not always show information on detecting oil palm trees correctly. Several points still show detection errors, such as incorrect oil palm tree position and oil palm trees that are not detected. This can happen because the software works based on templates without relying on user assistance.



a) b) c)

Figure 10. DTM creation results: a) homogeneoud sample; b) semi-homogenenous sample; c) heterogeneous sample



a) b) c)

Figure 11. DSM creation results: a) homogeneoud sample; b) semi-homogenenous sample; c) heterogeneous sample

Identification of the extraction results of oil palm trees needs to be completed to determine the performance of the software, which will later be used as a basis for estimateing tree height. The tolerance used in this software model performance test is 80% of the entire model (Ernawa, 2020; Nauthika et al., 2017; Oya et al., 2022).

Table 2. Result of identification and performance testing of oil palm tree calculations with eCognition Developer

Sample	Result	FP	FN	TP	F1-score
Homogeneous	522	24	52	498	92.91%
Semi-homogeneous	517	103	102	414	80.15%
Heterogeneous	494	52	61	442	88.66%

Figure 13 shows the results of automatic extraction using eCognition Developer. Table 2 shows the results of identification and performance tests of automatic extraction of ground truth data. With template matching from the template matching algorithm, oil palm tree detection can be done quickly. Based on the results of automatic extraction of oil palm trees using the template matching algorithm in eCognition Developer, the extraction results showed that 522 points were detected by trees in homogeneous samples, 517 points were detected by trees in semi-homogeneous samples, and 494 points were detected by trees in heterogeneous samples.

Table 3. Result of identification and performance testing of oil palm tree calculations with eCognition OPA

Sample	Result	FP	FN	TP	F1-score
Homogeneous	522	5	33	517	96.45%
Semi-homogeneous	509	40	47	469	91.51%
Heterogeneous	520	28	11	492	96.18%

Figure 14 shows the results of automatic extraction using eCognition OPA. Table 3 shows the results of identification and performance tests of automatic extraction of ground truth data. Oil palm tree extraction uses the help of eCognition OPA (Oil Palm Application) software, which is software that uses a OBIA method as its working principle. With eCognition OPA, you only need to enter aerial photo data or image data to be extracted. After that, the software will automatically process it itself without help from the user. Based on the results of automatic extraction of oil palm trees with eCognition OPA, the extraction results showed that 522 points were detected by trees in homogeneous samples, 509 points were detected by trees in semi-homogeneous samples, and 520 points were detected by trees in heterogeneous samples.

Based on the performance test calculations that have been carried out, it can be concluded that the results of oil palm tree extraction using eCognition Developer and eCognition OPA in three sample areas reached a tolerance

a) b) c)

Figure 13. Results of automatic extraction using eCognition Developer: a) homogeneous sample; b) semi-homogenenous sample; c) heterogeneous sample

a) b) c)

Figure 14. Results of automatic extraction using eCognition OPA: a) homogeneous sample; b) semi-homogenenous sample; c) heterogeneous sample

of 80%. Therefore, these results can be used as a basis for further processing, namely determining the estimated height of oil palm trees.

4.3. Accuracy test results comparing the position and elevation of oil palm trees againtst ground truth data

Extraction of X and Y coordinates is carried out to see differences in the position of points resulting from automatic extraction of ground truth data, which will later be used as a basis for determining tree height estimates. Elevation information obtained from DTM and DSM is used to calculate the height value of the object, which in this study is the height of the oil palm tree. The height of an oil palm tree object can be determined based on the CHM (Canopy Height Model) value resulting from DSM subtraction minus DTM. In this stage, only oil palm trees that are identified correctly or with true positive information are used in comparisons and calculations. The results of comparing the differences in coordinates and tree heights resulting from automatic extraction using eCognition Developer and eCognition OPA carried out comparison accuracy tests for palm oil against comparative data. From the overall position accuracy test results for extracted oil palm trees using eCognition Developer, each area sample is shown with the RMSe value.

In general, based on the positional accuracy of the three samples, namely homogeneous, semi-homogeneous and heterogeneous, the results of extraction and identification of oil palm trees using eCognition OPA software, as shown in Table 4, display better results than extraction results using eCognition Developer as shown in Table 5. This is indicated by the lower total RMSe value for the X coordinates and Y coordinates. A low RMSe value indicates a slight difference in position, where the automatic extraction point is close to the ground truth point of the comparison data, which is right in the middle of the tree canopy. The RMS value is produced by extracting the coordinate positions of the tree detection points from ground truth data shown in Figure 15.

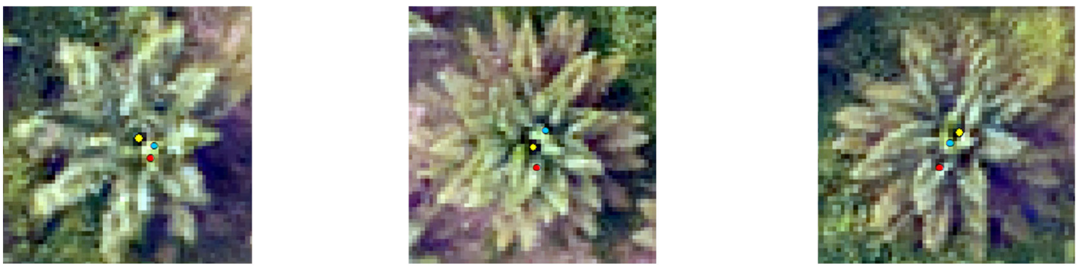
The accuracy test results of the palm oil height eCognition Developer are shown in Table 6. In contrast, the accuracy test results of the palm oil height eCognition OPA are shown in Table 7. Based on the high accuracy of the objects from the three samples used, namely homogeneous, semi-homogeneous and heterogeneous, the results of extraction and identification of oil palm trees using eCognition Developer software show a lower RMSe for homogeneous samples than the results of extraction and identification of oil palm trees using eCognition OPA software. Even in semi-homogeneous and heterogeneous samples, the RMSe value extracted from eCognition OPA

Table 4. Result of eCognition Developer palm trees positional accuracy test results

Sample	Quantity (m)		Averange (m)		RMSe	
	X	Y	X	Y	X	Y
Homogeneous	219.2949	311.6724	0.440351	0.625848	0.589866	0.799792
Semi-homogeneous	359.4366	164.6505	0.868204	11.76075	1.321718	0.554072
Heterogeneous	234.9702	234.0609	0.531607	0.52955	0.717642	0.68366

Table 5. Result of eCognition OPA palm trees positional accuracy test results

Sample	Quantity (m)		Averange (m)		RMSe	
	X	Y	X	Y	X	Y
Homogeneous	322.461	223.2803	0.623716	0.431877	0.751461	0.568819
Semi-homogeneous	229.8462	201.5261	0.489035	0.428779	0.608721	0.538584
Heterogeneous	223.8648	0.45501	0.411863	0.52955	0.564563	0.511867



a) b) c)

Figure 15. Overview of the differences between the positions of eCognition Developer and eCognition OPA

Table 6. Accuracy test results of palm oil tree height eCognition Developer

Sample	Quantity h (m)	Averange h (m)	RMSe h
Homogeneous	263.2901	0.528695	0.771848
Semi-homogeneous	237.24	0.573044	0.904406
Heterogeneous	273.6	0.619005	1.05175

Table 7. Accuracy test results of palm oil tree height eCognition OPA

Sample	Quantity h (m)	Averange h (m)	RMSe h
Homogeneous	298.9299	0.578201	0.841973
Semi-homogeneous	242.6201	0.516213	0.777238
Heterogeneous	249.5101	0.507134	0.021189

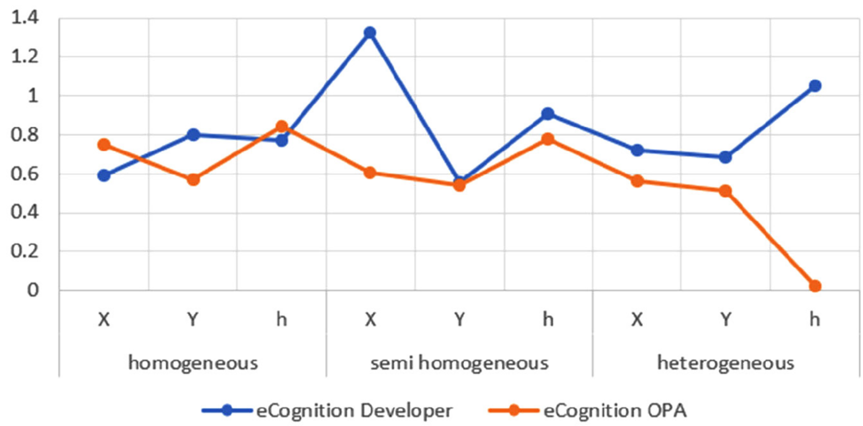


Figure 16. RMSe eCognition Developer and eCognition OPA chart

shows lower results than the extraction results from eCognition Developer. Based on this, the overall the object height from eCognition OPA shows better results than object height from eCognition OPA.

The distribution of RMSe is shown in Figure 16. From the accuracy of the position and height of the resulting object, many of the positions of points extracted from oil palm trees using eCognition Developer and eCognition OPA are not at the center point of the oil palm tree canopy which is used as a reference in determining tree height estimates. Therefore, there is still a point shift, as indicated by the RMSe value. Based on this, the estimated value of tree height is greatly influenced by the position of the extraction point.

5. Conclusions

Our study concluded that integration of aerial photography and LiDAR data can be used to determine position in estimating the height of oil palm trees. The results of automatic calculation oil palm trees using eCognition Developer and eCognition OPA can be used as an alternative for calculating oil palm trees on land with homogeneous, semi-homogeneous and heterogeneous characteristics where the performance results of both software reach more than 80%. The results of the automatic extraction of oil palm trees are in the form of points showing information about the position of X and Y coordinates. Overall, the RMSe value of position and height extracted using eCognition OPA is smaller than eCognition Developer for 3 samples, namely homogeneous, semi-homogeneous and heterogeneous.

Based on the performance test results for calculating the number of trees, and testing the accuracy of the position and height of trees resulting from automatic extraction with eCognition Developer and eCognition OPA, it can be used as an alternative in determining tree height. The automatic extraction results of eCognition OPA show better results for tree height estimation than eCognition Developer.

Acknowledgements

The authors thanks to the Geospatial Information Agency for data used in this research.

Author contributions

Lutfi'ah Noviani Rohmah: conceptualizition, methodology, data curation, formal analysis, visualization and writing – original draft. Naufal Setiawan: methodology, validation, supervision, writing – reviewing. Mochamad Irwan Hariyono: data curation, validation, supervision, writing – reviewing. Agung Syetiawan: supervision, writing – original draft, writing – reviewing.

References

Abidin, Z. H., Andreas, H., Maulana, D., Hendrasto, M., Gamal, M., & Suganda, O. K. (2004). Penentuan tinggi orthometrik Gunung Semeru berdasarkan data survei GPS dan Model Geoid EGM 1996 [Determination of the orthometric height of Mount Semeru based on GPS survey data and the 1996 EGM Geoid Model]. *Journal of Mathematical and Fundamental Sciences*, *36*(2), 145–157. https://doi.org/10.5614/itbj.sci.2004.36.2.4

Alexander, C., Korstjens, A. H., & Hill, R. A. (2018). Influence of micro-topography and crown characteristics on tree height estimations in tropical forests based on LiDAR canopy height models. *International Journal of Applied Earth Observation and Geoinformation*, *65*, 105–113. https://doi.org/10.1016/j.jag.2017.10.009

Badan Pusat Statistik. (2017). *Statistik kelapa sawit Indonesia 2017* [Indonesian palm oil statistics 2017]. https://www.bps.go.id/id/publication/2018/11/13/b73ff9a5dc9f8d694d74635f/statistik-kelapa-sawit-indonesia-2017.html

Ernawa, Y. G. (2020). *Perhitungan pohon pada perkebunan kelapa sawit menggunakan software trimble ecognition developer dari citra foto udara* (*Studi kasus*: *Muara Bengkal*, *Kutai Timur*, *Kutai Kartanegara*, *Kalimantan Timur*) [Tree calculation on oil palm plantations using trimble ecognition developer software from aerial photographic images (Case study: Muara Bengkal, East Kutai, Kutai Kartanegara, East Kalimantan] [Doctoral dissertation, Institut Teknologi Nasional Malang].

Featherstone, W. E., & Kuhn, M. (2006). Height systems and vertical datums: A review in the Australian context. *Journal of Spatial Science*, *51*(1), 21–41. https://doi.org/10.1080/14498596.2006.9635062

Federal Geographic Data Committee. (1998). *Geospatial positioning accuracy standards part 3*: *National Standard for spatial data accuracy* (FGDC Standard No. FGDC-STD-007.3-1998). https://www.fgdc.gov/standards/projects/accuracy/part3/index_html

Hamdani, H., Septiarini, A., Sunyoto, A., Suyanto, S., & Utaminingrum, F. (2021). Detection of oil palm leaf disease based on color histogram and supervised classifier. *Optik*, *245*, Article 167753. https://doi.org/10.1016/j.ijleo.2021.167753

Hao, J., Li, X., Wu, H., Yang, K., Zeng, Y., Wang, Y., & Pan, Y. (2023). Extraction and analysis of tree canopy height information in high-voltage transmission-line corridors by using integrated optical remote sensing and LiDAR. *Geodesy and Geodynamics*, *14*(3), 292–303. https://doi.org/10.1016/j.geog.2022.11.008

Hao, Y., Zhen, Z., Li, F., & Zhao, Y. (2019). A graph-based progressive morphological filtering (GPMF) method for generating canopy height models using ALS data. *International Journal of Applied Earth Observation and Geoinformation*, *79*, 84–96. https://doi.org/10.1016/j.jag.2019.03.008

Hashim, S. A., Daliman, S., Rodi, I. N. M., Aziz, N. A., Amaludin, N. A., & Rak, A. E. (2020). Analysis of oil palm tree recognition using drone-based remote sensing images. *IOP Conference Series*: *Earth and Environmental Science*, *596*, Article 012070. https://doi.org/10.1088/1755-1315/596/1/012070

Held, A., Ticehurst, C., Lymburner, L., & Williams, N. (2003). High resolution mapping of tropical mangrove ecosystems using hyperspectral and radar remote sensing. *International Journal of Remote Sensing*, *24*(13), 2739–2759. https://doi.org/10.1080/0143116031000066323

Irsanti, D., Sasmito, B., & Bashit, N. (2019). Kajian pengaruh penajaman citra untuk perhitungan jumlah pohon kelapa sawit secara otomatis menggunakan foto udara (Studi kasus: KHG Bentayan Sumatra Selatan) [Stydy of the effect of image sharpening on automation calculation of the number of oil palm trees using aerial photographs (Case study: KHG Bentayan, South Sumatra)]. *Jurnal Geodesi Undip*, *8*(1), 428–434.

Khosravipour, A., Skidmore, A. K., Wang, T., Isenburg, M., & Khoshelham, K. (2015). Effect of slope on treetop detection using a LiDAR Canopy Height Model. *ISPRS Journal of Photogrammetry and Remote Sensing*, *104*, 44–52. https://doi.org/10.1016/j.isprsjprs.2015.02.013

Kipli, K., Osman, S., Joseph, A., Zen, H., Awang Salleh, D. N. S. D., Lit, A., & Chin, K. L. (2023). Deep learning applications for oil palm tree detection and counting. *Smart Agricultural Technology*, *5*, Article 100241. https://doi.org/10.1016/j.atech.2023.100241

Li, F., Zhu, H., Luo, Z., Shen, H., & Li, L. (2021). An adaptive surface interpolation filter using cloth simulation and relief amplitude for airborne laser scanning data. *Remote Sensing*, *13*(15), Article 2938. https://doi.org/10.3390/rs13152938

Lourenço, P., Teodoro, A. C., Gonçalves, J. A., Honrado, J. P., Cunha, M., & Sillero, N. (2021). Assessing the performance of different OBIA software approaches for mapping invasive alien plants along roads with remote sensing data. *International Journal of Applied Earth Observation and Geoinformation*, *95*, Article 102263. https://doi.org/10.1016/j.jag.2020.102263

Münzinger, M., Prechtel, N., & Behnisch, M. (2022). Mapping the urban forest in detail: From LiDAR point clouds to 3D tree models. *Urban Forestry* & *Urban Greening*, *74*, Article 127637. https://doi.org/10.1016/j.ufug.2022.127637

Norzaki, N., & Tahar, K. N. (2019). A comparative study of template matching, ISO cluster segmentation, and tree canopy segmentation for homogeneous tree counting. *International Journal of Remote Sensing*, *40*(19), 7477–7499. https://doi.org/10.1080/01431161.2018.1524182

Nauthika, T. A., Suprayogi, A., & Sudarsono, B. (2017). Identifikasi dan estimasi tingkat produktivitas kelapa sawit menggunakan teknologi LiDAR (Studi kasus: Air Upas, Kabupaten Ketapang) [Identification and estimation of palm oil productivity level using LiDAR technology (Case study: Air Upas, Ketapang Regency)]. *Jurnal Geodesi Undip*, *6*(4), 254–262.

Nurmasari, Y., & Wijayanto, A. W. (2021). Oil palm plantation detection in indonesia using Sentinel-2 and Landsat-8 optical satellite imagery (Case study: Rokan Hulu Regency, Riau province). *International Journal of Remote Sensing and Earth Sciences* (*IJReSES*), *18*(1), 1–18. https://doi.org/10.30536/j.ijreses.2021.v18.a3537

Nyland, R. D. (2016). *Silviculture*: *Concepts and applications* (3rd ed.). Waveland Press.

Okojie, J. A., Okojie, L. O., Effiom, A. E., & Odia, B. E. (2020). Relative canopy height modelling precision from UAV and ALS datasets for forest tree height estimation. *Remote Sensing Applications*: *Society and Environment*, *17*, Article 100284. https://doi.org/10.1016/j.rsase.2019.100284

Oya, N., Fazlina, Y. D., & Rusdi, M. (2022). Analisis citra resolusi menengah untuk menghitung tanaman kelapa sawit [Medium resoliution image analysis for counting oil palm plants]. *Jurnal Ilmiah Mahasiswa Pertanian*, *7*(3), 463–466.

Peynaud, E., & Momo Takoudjou, S. (2024). Terrestrial LiDAR point cloud dataset of cocoa trees grown in agroforestry systems in Cameroon. *Data in Brief*, *53*, Article 110108. https://doi.org/10.1016/j.dib.2024.110108

Priambodo, D. A., Tjahjadi, M. E., & Suhari, K. T. (2022). Pembuatan model 3D jalan raya Bayat Untuk keperluan existing menggunakan metode foto udara (UAV) di Klaten [Creation of a 3D model of Bayat Highway for existing purposes using aerial photography (UAV) method in Klaten]. *Teras Jurnal*: *Jurnal Teknik Sipil*, *12*(1), 177–190. https://doi.org/10.29103/tj.v12i1.654

Purnamasayangsukasih, P. R., Norizah, K., Ismail, A. A. M., & Shamsudin, I. (2016). A review of uses of satellite imagery in monitoring mangrove forests. *IOP Conference Series*: *Earth and Environmental Science*, *37*, Article 012034. https://doi.org/10.1088/1755-1315/37/1/012034

Putra, Y. C., & Wijayanto, A. W. (2023). Automatic detection and counting of oil palm trees using remote sensing and object-based deep learning. *Remote Sensing Applications*: *Society and Environment*, *29*, Article 100914. https://doi.org/10.1016/j.rsase.2022.100914

Rizeei, H. M., Shafri, H. Z. M., Mohamoud, M. A., Pradhan, B., & Kalantar, B. (2018). Oil palm counting and age estimation from WorldView-3 imagery and LiDAR data using an integrated OBIA height model and regression analysis. *Journal of Sensors*, Article 2536327. https://doi.org/10.1155/2018/2536327

Sastrosayono, S. (2003). *Budi daya kelapa sawit* [Oil palm cultivation]. AgroMedia.

Smith, A. M. S., Strand, E. K., Steele, C. M., Hann, D. B., Garrity, S. R., Falkowski, M. J., & Evans, J. S. (2008). Production of vegetation spatial-structure maps by per-object analysis of juniper encroachment in multitemporal aerial photographs. *Canadian Journal of Remote Sensing*, *34*(sup2), S268–S285. https://doi.org/10.5589/m08-048

Susanti, A., & Maryudi, A. (2016). Development narratives, notions of forest crisis, and boom of oil palm plantations in Indonesia. *Forest Policy and Economics*, *73*, 130–139. https://doi.org/10.1016/j.forpol.2016.09.009

Syetiawan, A., & Haidar, M. (2019). Pemetaan perkebunan sawit rakyat dari foto udara nonmetrik menggunakan analisis berbasis objek [Mapping of smallholder oil palm plantations from non-metric aerial photographs using-object based analysis]. *Majalah Ilmiah Globë*, *21*(1), 53–62.

Wang, H., Seaborn, T., Wang, Z., Caudill, C. C., & Link, T. E. (2021). Modeling tree canopy height using machine learning over mixed vegetation landscapes. *International Journal of Applied Earth Observation and Geoinformation*, *101*, Article 102353. https://doi.org/10.1016/j.jag.2021.102353

Webster, C., Essery, R., Mazzotti, G., & Jonas, T. (2023). Using just a canopy height model to obtain lidar-level accuracy in 3D forest canopy shortwave transmissivity estimates. *Agricultural and Forest Meteorology*, *338*, Article 109429. https://doi.org/10.1016/j.agrformet.2023.109429

Wolf, P. R. (1978). [Review of the book Elements of photogrammetry (with air photo interpretation and remote sensing]. *International Journal of Rock Mechanics and Mining Sciences* & *Geomechanics Abstracts*, *15*(1), A22. https://doi.org/10.1016/0148-9062(78)90936-1

Yun, T., Jiang, K., Li, G., Eichhorn, M. P., Fan, J., Liu, F., Chen, B., An, F., & Cao, L. (2021). Individual tree crown segmentation from airborne LiDAR data using a novel Gaussian filter and energy function minimization-based approach. *Remote Sensing of Environment*, *256*, Article 112307. https://doi.org/10.1016/j.rse.2021.112307

Zhang, W., Qi, J., Wan, P., Wang, H., Xie, D., Wang, X., & Yan, G. (2016). An easy-to-use airborne LiDAR data filtering method based on cloth simulation. *Remote Sensing*, *8*(6), Article 501. https://doi.org/10.3390/rs8060501

Zhang, Z., Gerke, M., Vosselman, G., & Yang, M. Y. (2018). Filtering photogrammetric point clouds using standard LiDAR filters towards DTM generation. *ISPRS Annals of the Photogrammetry*, *Remote Sensing and Spatial Information Sciences*, *IV–2*, 319–326. https://doi.org/10.5194/isprs-annals-IV-2-319-2018

Zhou, L., Meng, R., Tan, Y., Lv, Z., Zhao, Y., Xu, B., & Zhao, F. (2022). Comparison of UAV-based LiDAR and digital aerial photogrammetry for measuring crown-level canopy height in the urban environment. *Urban Forestry* & *Urban Greening*, *69*, Article 127489. https://doi.org/10.1016/j.ufug.2022.127489