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Automatic Pine Tree Calculation Using You Only Look Once (YOLO)

Pengiraan Automatik Pokok Pain Menggunakan *You Only Look Once* (YOLO)

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ABSTRACT

Counting pine trees from aerial imagery photos is an important challenge in a variety of fields, including ecology, forest management, and climate change Traditional methods of tree counting often require time-consuming and cost-effective field surveys. Therefore, there is a need for a more efficient and accurate method for counting Pine trees from aerial imagery photos. This study has carried out a more efficient and accurate calculation of automatic pine trees, using the YOLOv8 detection model, which aims to detect pine trees by comparing YOLOv8 and Local Maxima in previous studies. The results obtained in this study are that the YOLOv8 model can detect pine tree objects with an accuracy of 88.8%, the precision in the Pines-tree class reaches 88.25 and the recall reaches 96.9%. Meanwhile, for the Null class, the precision value reached 61.5% and the recall reached 81.9%. From the accuracy results obtained, it shows that the YOLOv8 model succeeds in detecting and counting pine trees better than previous studies.

Keywords: Aerial imagery; Local Maxima; Pine calculation; Pine tree; YOLOv8

INTRODUCTION

Forests are one of the sectors in agriculture that has great potential. In 2019 it contributed 25.71% to the agricultural industry and 3.27% to the total GDP (Nurhabib et al., 2022). One of the forests that has various benefits is pine or commonly known as tusam, pine provides many benefits both ecologically and economically, namely preventing erosion and flooding for ecological benefits, while economically it is as a producer of wood and sap (Negara et al., 2019). Derivative products of pine sap, which is a type of non-timber forest product (NTFP), have entered the international trade system where pine sap, namely gondorukem and turpentine, Indonesia occupies the third position in the international market, after China and Brazil (Audina et al., 2020). This shows the lot of potential that can be obtained from pine forests.

One of the main centers of pine forest population in West Java is located in Sukabumi, which includes several sub-districts, including: Sagaranten District, Bojong Lopang District, Jampang District, and Pelabuhan Ratu District. Pine forest management in this area is carried out in various production forest areas (Lestari et al., 2023). Counting pine trees from aerial imagery photos is an important challenge in a variety of fields, including ecology, forest management, and climate change (Lestari et al., 2023). Traditional methods of tree counting often require time-consuming and costly field surveys. Therefore, there is a need for a more efficient and accurate method for counting Pine trees from aerial imagery photos (Arrofiqoh & Harintaka, 2018), (Prasvita et al., 2021). Previous research conducted calculations on oil palm trees using algorithms canopy height model (CHM) and local maxima (LM), the results obtained are that it can detect oil palm trees automatically with an accuracy of 94.3% for the optimal class, 84.5% for the medium class and 91.9% for the rare class (Srinarta et al., 2022). In addition, using the CHM and LM methods is also used for the calculation of pine trees with the result being a minimum class of 4 meters which is 65.8% while a minimum class of 3 meters is 80.6% (Lestari et al., 2023). Automatic detection of trees on oil palm plantation images using the convolutional neural network (CNN) on geographic information systems, generating value F1 Score for the training data process by 84%. Average score F1 Score for test data is 71% (Samuel et al., 2022).

Related research using deep learning namely the YOLO algorithm to count and detect oil palm trees in the IPB-Cargill oil palm area, obtained an accuracy value of 85.6%, 98.9% for precision, and 86.6% for Recall (Nurhabib et al., 2022). YOLOv8 is also used to detect and count oil palm trees, the results obtained are a precision value of 78.9% and a value of Recall 95,9% (Rahman et al., 2023). This study made an automatic pine tree calculation model using the You Only Look Once (YOLO) version 8 and compared the results of the calculation of pine trees with the local maxima. Comparison of the YOLOv8 method with local maxima in this study because the accuracy and calculation of the tree is greater and more precise than the local maxima (Srinarta et al., 2022), (Armanto et al., 2024). The model is expected to accurately calculate the number of pine trees by installing a filter Canopy Height Model.

PROBLEM STATEMENT

From the introduction above, several formulations of the problem can be compiled as follows:

1. How to leverage YOLOv8 to build a pine tree prediction model?
2. How do you compare the prediction results of the model obtained using YOLOv8 with the model that uses local maxima to detect pine trees?

LITERATURE REVIEW

Table 1: Literature review

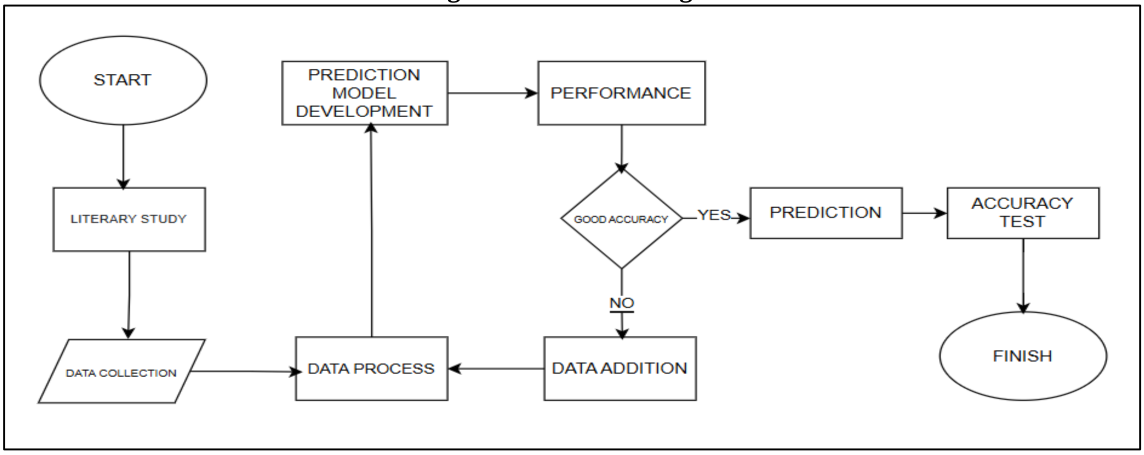
No	Author, Journal	Result	Conclusion
1.	Sinta Lestari, Erwin Hermawan, Sahid Agustian H, 2023 "Analysis of individual calculations on pine trees using the Local Maxima method from UAV (Unmanned Aerial Vehicle) images"	The study showed that using the local maxima method, as many as 4,166 trees were identified in the minimum class of four meters, while in the same class, the green ratio method identified 4,011 trees. In the three-meter minimum class, both the local maxima method and the green ratio each identified 4,731 trees.	Using pine tree data and different methods can be a reference for accuracy test calculations.
2.	Nurhabib, K. B. Seminar, Sudradjat 2022. "Recognition And Counting Of Oil Palm Tree With Deep	The training loss value of the graph is 0.6, which is close to zero, indicating that the model is quite effective in	From this study, the Convolutional Neural Network method can be used for tree calculation with aerial imagery.

	Learning Using Satellite Image"	recognizing oil palm objects.	
3.	Samuel, Kestrilia Rega Prilianti, Hendry Setiawan, Prasetyo Mimboro. 2022. "Automatic Tree Tree Detection Method in Oil Palm Plantation Imagery Using Convolutional Neural Network (CNN) Model in Geographic Information System Software"	The model trained using UAV imagery from the plantation in November 2021 proved to be the best model with an F1-Score of 84% during the training process. For the test data, the average F1-Score score obtained was 71%.	Based on the discussion of the implementation of Convolutional Neural Network with a training process of 84%, it can be applied to different aerial photo images.
4.	Muhammad Ruhiyatna Rahman, Riny Kusumawati, Fety Fatimah. 2023 "Object Detection Tree Counting Palm Oil Using Deep Learning Metodh"	The calculation of the number of oil palm trees from aerial satellite imagery using YOLOv8 resulted in a model with a precision of 0.79% and a recall of 0.96%.	In this study, a tree calculation model has been produced using the Convolutional Neural Network (CNN) method using the YOLOv8 algorithm.
5.	Kharisma Srinarta, Yudo Prasetyo, Firman Hadi. 2023 "Analysis of the Calculation of the Number of Oil Palm Trees Based on the Canopy Height Model (CHM) and Local Maxima (LM) Algorithms	In this study, oil palm tree calculations have been carried out using the canopy height model (CHM) and local maxima.	This study applied a canopy height model (CHM) used to filter low points.

METHODOLOGY

This research was conducted using data on pine forest areas in the IPB-Cargill oil palm area and additional data from the roboflow universe, there are several steps during this research ranging from data collection, data preprocessing to accuracy tests which can be seen in Figure 1.

Figure 1: Research stages



Data Collection

In this study, secondary and primary pine tree image data was collected, primary data is pine tree satellite image data obtained directly from the first source or direct observation in the field and secondary data is obtained from the roboflow universe. Satellite image data is 13704×21243 and pine tree image data from the roboflow universe is 640×640. The total data collected was 1213, secondary data was 1093 and primary data was one.

Preprocess Data

In the pre-data processing stage, several important steps are taken to prepare the image before it is used in model training. The first step is to clip the image using a fishnet with grids of 7×7, 8×8, 5×5, and 5×6 resulting in 120 smaller parts of the image. This process is done to increase the number of samples available and ensure that the model can learn from more variations in the data. Once this image is clipped, the next step is to tag it using roboflow. Image marking is carried out by labeling each object to be identified, after marking it is then resized the image to 640×640 and augmentation is added so that the number of images increases to 2869 images. Then the data is split into 3 parts, namely 70% for training data, 20% for validation data and 10% for test data, by adding data augmentation so that the data becomes more varied and makes the number of images three times more which then changes the percentage of data split to 88% of training data with the number of images 2509, 8% of validation data with the number of images 238, and 4% of test data with a total of 122 images.

Development of Prediction Models

After the data is tagged then the data is trained and validated to ensure that the model can train the dataset properly conducted in the google collaboratory, previously the data has been prepared to be trained as many as 2869 images with 50 epochs.

Performance

After the model is completed trained and validated, the next step is to test the model using test data that the model has never seen before during the training process. This test data is important for evaluating the model's performance against new data that has never been seen before as well as calculating confusion matrix that have value true positive (HCMC), true negative (TN), false positive (FP), and false negative (FN). From these values, accuracy, precision and recall according to Equations (1), (2) and (3) (Sary et al., 2023), (Hayati et al., 2023), (Ma'aruf & Hardjianto, 2023).

$$Akurasi = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

Data Addition

This stage is an additional data if the results of the performance are not good or below 70%, then pine tree datasets are added so that the dataset is more varied. After the data is added, it then returns to the pre-processing stage of data and model development so that it obtains good accuracy.

Predictions

Pine tree detection is carried out locally using a pine tree detection model that has been trained with YOLOv8 and has a pytorch (.pt) format, this detection changes dictionary detection results to get the image coordinate point at each angle box detection. Then the coordinate transformation is carried out from the image coordinate point to the UTM coordinate point (universal transverse mercator) by adding a filter Canopy Height Model (Simonetti et al., 2023). Scan to remove the constricted points, which is then done import Inside the GDF (geo data frame) and done Export into the form shapefile.

After exporting it into shapefile, it checks the results of the points detected by the model and ensures that the model can detect objects from the clipped image. If the model has detected all objects in the clipped image, then proceed to the accuracy test stage, but if the model cannot detect all objects from the clipped image, then return to the preprocessing data stage.

Accuracy Test

The accuracy test is carried out by calculating Error less and Error more on the pine tree canopy using the formula of Equations 4, 5 and 6 (Armanto et al., 2024). This process involves taking four samples with criteria determined using the purposive sampling, such as pine tree density, clearly visible pine tree canopy, size rectangle 80×75 meters, as well as the simple random sampling with an error limit of 2.6% of the total population of 6460 to ensure the level of detection accuracy generated by the model (Lenaini, 2021). Thus, this evaluation provides a clearer picture of the model's performance in precisely detecting the pine tree canopy until the model gains better accuracy.

$$Commission\ error = \frac{Error\ Lebih}{Error\ Lebih + Jumlah\ Benar} \tag{4}$$

$$Omission\ error = \frac{Error\ Kurang}{Error\ Kurang + Jumlah\ Benar} \tag{5}$$

$$Accuracy = \frac{Jumlah\ Benar}{Total\ Referensi + Error\ Lebih} \tag{6}$$

RESULTS AND DISCUSSION

This study uses the You Only Look Once (YOLO) version 8 model for the detection of pine trees. There are two methods applied to determine the detected points on pine trees, namely by applying a filter and without a filter.

Result

1. Applying Filters

At this stage, detection and addition of filters are carried out to eliminate each point that is not suitable, using a Canopy Height Model filter with a value of 0.8 meters. The trained model is used for this elimination stage, so that it can produce a prediction output from the model in the form of points in shapefile format.

Figure 2: Export detection results with filters

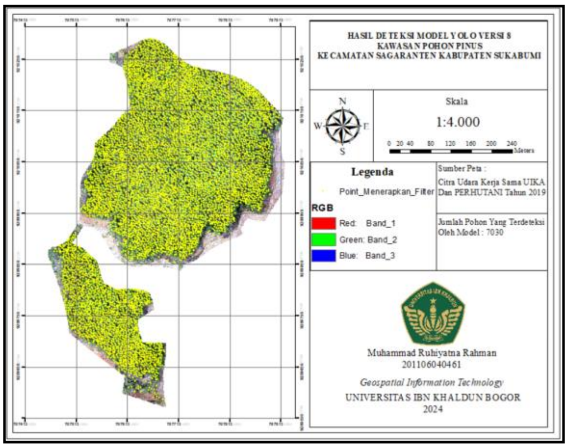


Figure 2 shows the results of a shapefile that has been processed to predict the number of pine trees. In this image, each detected pine tree is represented by yellow dots scattered throughout the area. Based on the predictions made, the total number of pine trees that have been successfully identified is 7030 trees.

2. No Filter

At this stage, predictions are made without adding a Canopy Height Model to the predictive model that has been trained, so that it can produce prediction output from the model in the form of points in shapefile format.

Figure 3: Export unfiltered detection results

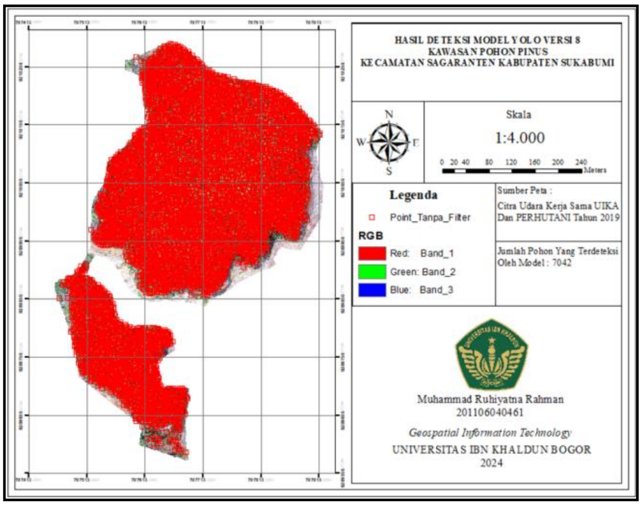


Figure 3 shows the results of a shapefile that has been processed to predict the number of pine trees. In this image, each detected pine tree is represented by a red box scattered throughout the area. Based on the predictions made, the total number of pine trees that have been successfully identified is 7042 trees.

Discussion

1. Apply filters

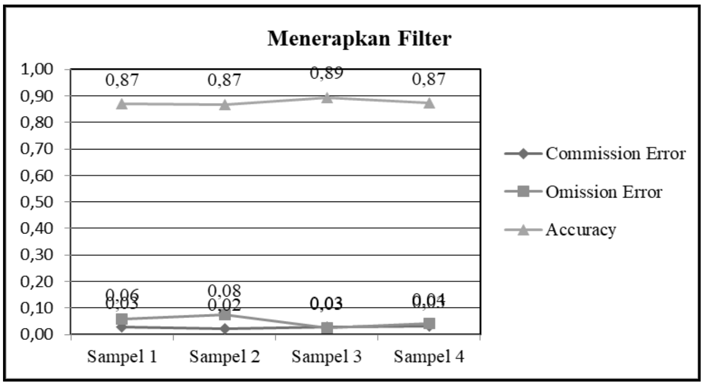
Model evaluation is carried out on sample data from the sample point which is automatically detected by the model and divided into four parts. The four parts are divided according to purposive sampling criteria, such as pine tree density, clearly visible pine tree canopy and rectangle size of 80×75 meters and a simple random sampling method with an error limit of 2.6% of the total pine population of 6460 to find more error points and less errors. The following is a table of test accuracy of each sample from the YOLOv8 method can be seen in Table 2.

Table 2: Accuracy test results by applying filters

Pine Tree Detection Model								
Area	**Total References**	**Classification Results**	***More Errors***	***Less Error***	**Sum True**	***Commission Error***	***Omission Error***	***Accuracy***
Sample 1	343	315	9	19	306	0,03	0,06	0,87
Sample 2	343	311	7	25	304	0,02	0,08	0,87
Sample 3	287	272	8	7	264	0,03	0,03	0,89
Sample 4	261	243	8	10	235	0,03	0,04	0,87
						0,03	**0,05**	**0,88**

Based on the results of the accuracy test of commission error and omission error with four samples shown in Table 2, it can be concluded that the accuracy results of the average sample are 88%, Commission error 3% and omission error 5%. The results of the accuracy graph can be seen in Figure 4.

Figure 4: Accuracy test graph by applying filters



This graph visualizes the results of four samples tested using commission error and omission error, it can be seen that sample 1 obtained an accuracy of 0.87, commission error 0.03 and omission error 0.06, sample 2 obtained an accuracy of 0.87, commission error 0.02 and omission error 0.08, sample 3 obtained an accuracy of 0.89, commission error 0.03 and Omission error 0.03 and sample 4 obtained an accuracy of 0.87, commission error 0.03 and omission error 0.04 Overall this graph shows that the model can detect pine trees with high accuracy values and fewer errors.

2. No Filter

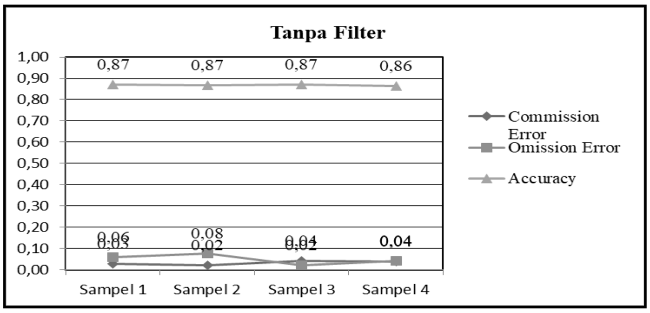
The prediction is made using a trained model, then a shapefile in the form of points is generated which produces 7042 points or points. The points generated by the model are evaluated and calculated for accuracy to determine the accuracy values, commission errors and omission errors in the sample that has been made. The following is the accuracy test table of each sample from the YOLOv8 method, while the accuracy test results are in Table 3.

Table 3: Unfiltered accuracy test results

Unfiltered Pine Tree Detection Model								
Area	**Total References**	**Classification Results**	***More Errors***	***Less Error***	**Sum True**	***Commision Error***	***Omission Error***	***Accuracy***
Sample 1	343	315	9	19	306	0,03	0,06	0,87
Sample 2	343	311	7	25	304	0,02	0,08	0,87
Sample 3	287	270	11	6	259	0,04	0,02	0,87
Sample 4	261	242	9	10	233	0,04	0,04	0,86
						0,03	**0,05**	**0,87**

Based on the results of the accuracy test of commission error and omission error with 4 samples shown in Table 4.3, it can be concluded that the accuracy results of the average sample are 87%, Commission error 3% and omission error 5%. The results of the accuracy graph can be seen in Figure 5.

Figure 5: Unfiltered accuracy test graph



This graph visualizes the results of 4 samples tested using commission error and omission error, can be seen in the 1st sample obtained an accuracy of 0.87, commission error 0.03 and omission Error 0.06. This study reinforces previous research that showed that the YOLOv8 model is more effective in detecting pine trees by providing better performance in terms of accuracy and more and more accurate tree calculations Compared to Local Maxima (Srinarta et al., 2022), (Armanto et al., 2024).

CONCLUSION

The results of the research regarding the detection of pine tree objects and the calculation of the number of pine trees using YOLOv8, can be concluded as follows:

1. The pine tree prediction model can predict pine tree objects with an accuracy of more than 88%. This accuracy value shows that the model obtained can detect pine trees well.
2. From the results of pine tree detection using a trained model, applying the Canopy Height Model filter, and an accuracy test was carried out, an average of four samples taken from commission error with a value of 0.03, omission error with a value of 0.05, and an accuracy of 0.88 then the accuracy range was 85.4% - 90.6% and the results of pine tree detection using a model that had been trained without applying a filter and an accuracy test was obtained The average of the four samples taken, namely commission error with a value of 0.03, omission error with a value of 0.05, and an accuracy of 0.87, the accuracy range is 84.4% - 89.6%, which indicates that using the YOLOv8 model is better than the accuracy test with the local maxima method, which is a minimum class of 3 meters high with a green ratio that obtains a commission error of 0.01, omission error 0.18 and accuracy value 0.80.

REFERENCES

Armanto, D. Y., Hudjimartsu, S. A., & Hermawan, E. (2024). Identify automatic oil palm tree calculations using the Convolutional Neural Network (CNN) method. Journal of Computer Engineering Students, 8(3), 2648–2654.

Arrofiqoh, E. N., & Harintaka, H. (2018). Implementation of Convolutional Neural Network Method for Classification of Plants on High-Resolution Images. Geomatics, 24(2), 61. https://doi.org/10.24895/jig.2018.24-2.810

Audina, N., Solihat, R. F., & Purwanto, A. (2020). The Effect of Age Class on the Productivity of Merkusii Pine Sap in North Bandung KPH. Wanamukti, 23(1), 10–21.

Hayati, N. J., Singasatia, D., & Muttaqin, M. R. (2023). Object Tracking uses the You Only Look Once (YOLO)v8 Algorithm to Count Vehicles. Computing: Scientific Journal of Computer and Informatics, 12(2), 91–99. https://doi.org/10.34010/komputa.v12i2.10654

Lenaini, I. (2021). Purposive sampling and snowball sampling techniques. Journal of Historical Education, Research & Development, 6(1), 33–39. http://journal.ummat.ac.id/index.php/historis

Lestari, S., Hermawan, E., & Hudjimartsu, S. A. (2023). Analysis of individual calculations on pine trees using the Local Maxima method from UAV (Unmanned Aerial Vehicle) images. Infotech Journal, 9(2), 586–595. https://doi.org/10.31949/infotech.v9i2.7101

Ma'aruf, A., & Hardjianto, M. (2023). Application of the You Only Look Once Version 8 Algorithm for Indonesian Sign Language Alphabet. National Seminar of Students of the Faculty of Information Technology, 2 (September), 567–576.

Negara, H. K., Rachmawati, N., & Payung, D. (2019). Identification of pine tree damage in the Banjarbaru City Forest. Sylva Scienteae Journal, 2(4), 635–644.

Nurhabib, I., Seminar, K. B., & Sudradjat. (2022). Recognition and counting of oil palm tree with deep learning using satellite image. IOP Conference Series: Earth and Environmental Science, 974(1). https://doi.org/10.1088/1755-1315/974/1/012058

Prasvita, D. S., Santoni, M. M., Wirawan, R., & Trihastuti, N. (2021). Classification of oil palm trees on lidar image fusion data and aerial photographs using convolutional neural networks. Scientific Journal of Informatics Research and Learning, 6(2), 406–415. https://doi.org/10.29100/jipi.v6i2.2437

Rahman, M. R., Kusumawati, R., & Fatimah, F. (2023). Object Detection Tree Counting Palm Oilusing Deep Learning Method. Bina: Journal of Regional Development, 2(1), 45–51.

Samuel, Prilianti, K. R., Setiawan, H., Mimboro, P., & Correspondence, P. (2022). The method of automatic detection of tree trees in oil palm plantation imagery uses the Convolutional Neural Network (CNN) model in geographic information system software. Journal of Information Technology and Computer Science, 9(7), 1689–1698. https://doi.org/10.25126/jtiik.202296772

Sary, I. P., Andromeda, S., & Armin, E. U. (2023). Performance Comparison of YOLOv5 and YOLOv8 Architectures in Human Detection using Aerial Images. Ultima Computing : Jurnal Sistem Komputer, 15(1), 8–13. https://doi.org/10.31937/sk.v15i1.3204

Simonetti, A., Araujo, R. F., Celes, C. H. S., Da Silva E Silva, F. R., Dos Santos, J., Higuchi, N., Trumbore, S., & Marra, D. M. (2023). Canopy gaps and associated losses of biomass - combining UAV imagery and field data in a central Amazon forest. Biogeosciences, 20(17), 3651–3666. https://doi.org/10.5194/bg-20-3651-2023

Srinarta, K., Prasetyo, Y., & Hadi, F. (2022). Analysis of the calculation of the number of oil palm trees based on the Canopy Height Model (CHM) and Local Maxima (LM) algorithms. Undip Geodesy Journal, 11(1), 51–60. https://ejournal3.undip.ac.id/index.php/geodesi/article/view/32315