Enhancing the Precision of Mangrove Area Estimation by Incorporating Canopy Gaps in UAV Methodologies

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Keywords: Mangroves, UAV, Canopy Gaps, Segmentation, OBIA

Abstract

One such coastal ecosystem that has various importance is mangrove. They provide biodiversity support, coastal protection, and carbon sequestration. One problem not well researched and known for accurate monitoring of mangrove forests is often hindered by the lack of consideration for canopy gaps, which significantly influence ecosystem dynamics, seedling recruitment, and overall forest health. This study enhances the precision of mangrove area estimation by integrating canopy gap identification using Unmanned Aerial Vehicle (UAV) imagery. After UAV acquisition, it would go through orthomosaic, and the following orthomosaic would be used for segmentation and Object-Based Image Analysis (OBIA). Conducted in the Lantebung & Untia Mangrove Tourism Area, South Sulawesi, Indonesia, the research employed UAV-based high-resolution RGB imagery to classify mangrove species and detect canopy gaps. Field validation and OBIA classification were used to improve accuracy, resulting in a refined methodology for calculating mangrove area while accounting for canopy gaps. The accuracy of the OBIA classification yielded good results in identifying and mapping the distribution of mangrove species. The overall accuracy is 80.65% for three classes: Rhizophora mucronate, Avicenna sp, and Canopy gaps. Findings reveal that canopy gaps, caused by natural and anthropogenic factors, impact mangrove structure and should be considered in monitoring and conservation strategies. The study introduces a novel formula for more accurate mangrove area estimation, demonstrating that traditional methods may overestimate coverage by ignoring gaps. These findings contribute to improved conservation planning and management of mangrove ecosystems, particularly in mixed-species environments where mapping accuracy remains challenging.

1. Introduction

Mangroves are a coastal ecosystem that functions as a reservoir of biodiversity, which is essential in supporting a wide range of life forms and providing a series of essential ecosystem services (K et al., 2024; Suhardi et al., 2024). Additionally, mangroves have the ability to maintain stability in coastal areas, support and even increase fisheries activities, and mitigate climate change through carbon absorption (IPCC, 2022; Kauffman et al., 2020). However, mangroves continue to experience degradation due to anthropogenic activities, which necessitates effective conservation and management efforts.

Mangrove area monitoring often overlooks canopy gaps. Although these gaps occupy a relatively small proportion of the total mangrove area, they are critical in influencing microhabitats, seedling recruitment, and ecosystem resilience (Cao et al., 2023; Imai et al., 2006). Accurate monitoring of mangrove canopy phenology is crucial for determining necessary rehabilitation actions (Cao et al., 2023).

Mangrove canopy gaps often occur due to natural ecosystem mechanisms and human activities (Duke, 2001). The forest's ecological aspect and physical conditions also change when canopy gaps form. Naturally, a recovery process will occur to restore the ecosystem to its original state, which has implications for regeneration and the recruitment of new trees(Amir et al., 2009; Runkle, 1985). Whitmore (1989) explains that the canopy gap cycle is divided into three phases: the formation of the canopy gap, the growth of new seedlings, and the closure of the canopy gap by mature trees (Whitmore, 1989). Naturally, the recovery time for mangrove areas to close these canopy gaps is around 30 years (Duke, 2001).

Mapping mangroves using UAV technology has been widely performed worldwide, often integrating machine learning in identifying mangrove cover and species types (Ngo, 2024; Yin et al., 2024). One of the classifications frequently used in identifying mangrove types is OBIA (Object-Based Image Analysis), which can locate mangrove species based on UAV imagery through segmentation and identification. OBIA has been widely proven to achieve higher accuracy compared than pixel-based classification (Almeida de Oliveira et al., 2024).

UAV (Unmanned Aerial Vehicle) technology can identify and map canopy gaps in mangrove areas (Yang et al., 2024). UAV is a better alternative than satellite due to the flexibility to fly anywhere, affordability, and higher resolution data (Li et al., 2024; Zimudzi et al., 2021). UAV imagery falls into the category of very high-resolution images, which enables mangrove classification down to the species level and allows for mangrove ecosystem mapping by adding canopy gap information into the estimation of mangrove area coverage (Fu et al., 2022; Lim et al., 2024; Pham et al., 2019).

This research proposes an approach to estimate mangrove areas more accurately using UAVs, which can provide very high-resolution mapping for identifying mangrove species and canopy gaps in mangrove areas. The results of this study can enhance the reliability of mangrove monitoring efforts, support data-driven conservation policies, and ultimately contribute to global climate change mitigation efforts for the preservation of coastal biodiversity in Indonesia.

2. Methodology

2.1 Study Area

The location of the mangrove area that is is in the Lantebung & Untia Mangrove Tourism Area (5° 4' 38.71" S, 119° 27' 58.79" E), included in the administrative area of Makassar City, South Sulawesi Province, Indonesia. The geographical location of the mangrove area is close to the residential and industrial areas of Makassar City, which would significantly impact the mangrove health due to anthropogenic activities around the area. This research began with UAV image recording on 16 September with a flight time of 08:00 - 10:15. The results of the UAV recording were then orthomosaic processed and used as orthomosaic survey material. We also conducted a UAV recording on 4 October with a flight time of 15:00 - 16:00 (UTC +8:00). The choice of UAV recording time is adjusted to the recommendations of Doukari et al. (2019), namely solar azimuth angle of 45° degrees.

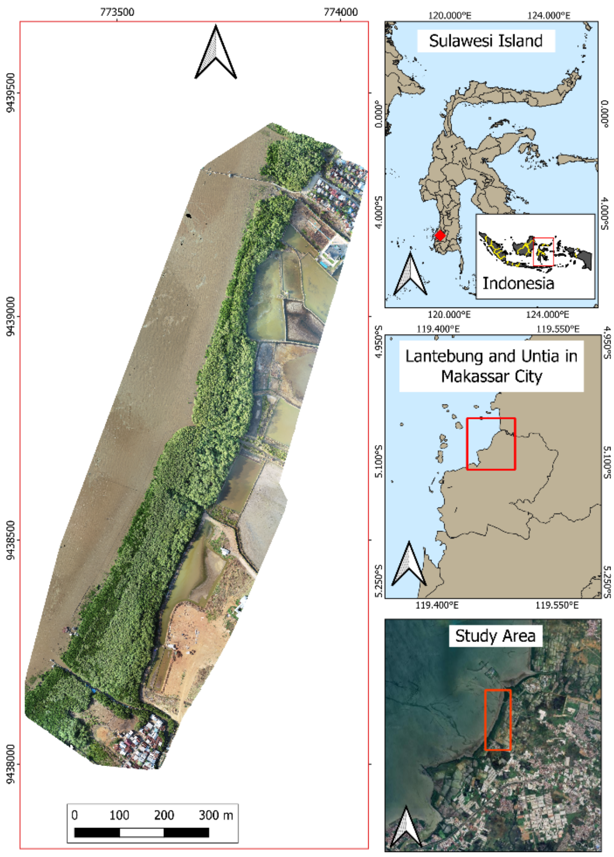

Figure 2. Study area and the UAV orthomosaic/

2.2 UAV Acquisition

For UAV image acquisition, we used a Phantom 4 Pro V2 Drone. Everything that we used on the UAV has not been modified in any way. The camera sensor is RGB**,** with a one-inch CMOS sensor and a lens with a FOV of 84° 8.8 mm/24 mm (35 mm format equivalent). The satellite positioning system used was the onboard module, which was GPS/GLONASS. The maximum flight time was 30 minutes, and the maximum wind speed resistance was 10 m/s (DJI, 2021).

Flight settings were set at an altitude of 100 m, side overlap, and forward overlap of 80%, with a drone speed setting of 9.9 M/S and a course angle of 203°. We determined the front and side overlap of 80%. In addition, the recording angle is set at 90°, which is perpendicular to the ground. We used DJI Terra to create and determine the UAV flight routes. The flight results produced a GSD (Ground Sample Distance) of 2.74 cm/pixel with a total covered area of 34.11 Ha. As a result of the large area and limited flight time due to the battery capacity, we had to divide into two flights. We also experimented on the best time to take the best pictures, and we eventually used second due to the image being brighter overall and higher quality. The first UAV acquisition (16 September) resulted in 669 images, and the second acquisition (4 October) resulted in 1162 images. The second acquisition we also experimented on was the flight UAV acquisition in DJI Terra, which was the oblique mode, so there were significantly more images taken with the same flight area.

UAV Acquisition	Total Images Taken	Flight Time
16th September 2024	669	08:00 – 10:15
4th October 2024	1162	15:00 – 16:00

Table 1. UAV imagery acquisition.

2.3 Pre-Processing

After acquiring the UAV images, the next step is creating an orthomosaic of the whole image. This UAV image process was done on Pix4dmapper. In general, there are three overall steps to generate the orthomosaic needed for further analysis: Initial Processing, Point Cloud and Mesh, DSM, Orthomosaic, and Index. For easier analysis, Pix4dmapper has a set of templates of the chosen parameters, which are: 3D Maps, 3D Models, Ag Multispectral, Ag Modified Camera, Ag RGB, 3D Maps – Rapid/Low Res, 3D Models – Rapid/Low Res, Ag RGB – Rapid/Low Res. We chose 3D Maps due to its various outputs (point cloud, 3D textured mesh, DSM, and orthomosaic) for further analysis and visualization (Pix4D, 2025). The 3D Map template complemented our goals to be more efficient time-wise, but its outputs are still deemed good for further analysis.

The important parameters for orthomosaic processing that we learned from trial and error are Point Cloud and Mesh. The parameters were an Image Scale of ½ (Half image size), optimal Point Density, and a minimum number of matches of three. The Point Cloud Densification parameters, as written above, we chose due to the complex homogenous mangrove canopy. Research done by Swayze & Tinkham (2022) shows that increased point cloud density results in higher data quality. Kameyama & Sugiura (2021) explain that the higher amount of point cloud

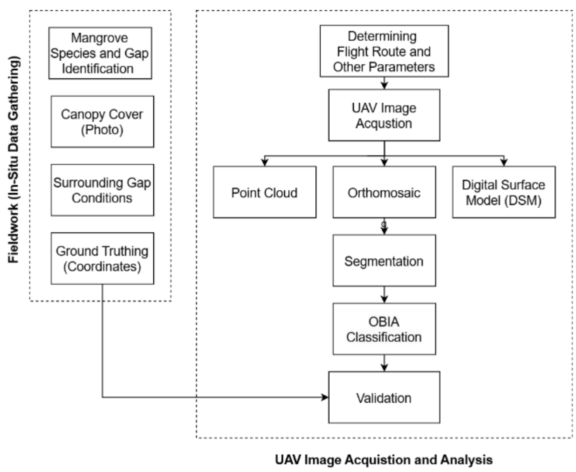

Figure 1. Flowchart of fieldwork and UAV image processing

density would result in a higher quality orthomosaic, which is what is needed to identify the canopy gaps.

2.4 Ground Truthing

Ground truthing evaluates the accuracy of image classification results by verifying them against real-world field data. For mapping mangrove species and gaps, we conducted ground truthing to test the accuracy of the image processing results. Points that will be used for classification are taken with the Avenza Maps application, which is available on Android & IOS.

For us, canopy gaps were defined as an opening of the canopy. Young canopy gaps, would usually have the tree still standing if there was a lightning strike or a fallen tree/s These trees would then create an opening through which light would pass through. Species effect, defined by Duke, is where a particular species would dominate or be more successful in its growth. Certain species would dominate and sometimes overlap with others; other times, there would be a gap due to height canopy differences. We did not categorize the gaps in this research canopy gaps as written above.

Due to the limited research on canopy gaps, there was no single method on reliably canopy gaps. Our method was to approach the canopy gaps and locate the individual/group of trees that had fallen or died. Duke (2001) mentions that gap creation, whilst unknown, can be caused by various factors such as the most common is lightning. Other causes may be due to wind, insects, pathogens, toxic chemicals, and anthropogenic causes such as logging (Amir et al., 2009; Duke, 2001). We also tried to identify the causes of the canopy gaps in our study area, but we cannot precisely determine the causes due to factors such as old trees that may have already been composed. This was a challenge for us because lightning strikes would be easily identifiable due to the burnt trees.

For efficiency, we determined the ground truthing for canopy gaps based on visual interpretation of UAV imagery and also recorded the ones we found while walking through the mangrove.

By UAV imagery, we determined there were 37 canopy gap points. Identification of Canopy gaps points was done by on-screen visual interpretation of the orthomosaic results when were doing our location check. Of the 37 gap points we determined, we only conducted field checks at 17 points due to the terrain conditions, limited time, and the reachability of each gap location. Of these 17 points that we checked in the field, 2 locations that we considered gaps through visual interpretation i n the orthomosaic were in fact, not gaps. In addition to the 17 that were done to verify the existence of the gaps, we recorded 81 ground points to map species of the mangrove area.

2.5 Segmentation and OBIA Classification

Segmentation and OBIA classification were done in eCognition Developer 64. We used a multiresolution segmentation algorithm. The algorithm introduced by Baatz & Schäpe (2000) partitioned images into objects with high accuracy using a region-growing technique. It begins by merging individual pixels

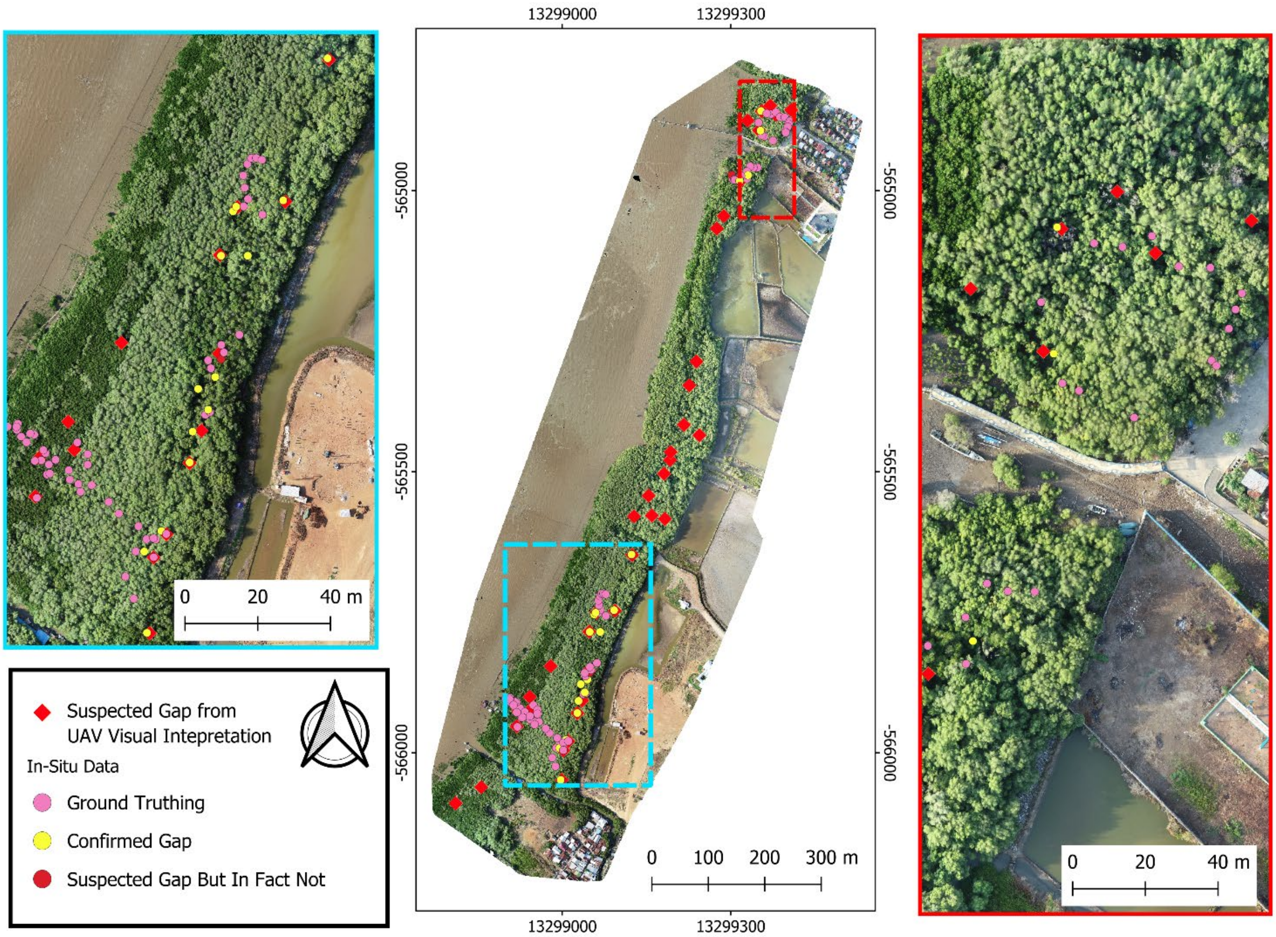

Figure 3. Canopy gaps identified from on-screen visual interpretation from UAV imagery overlaid with ground truthing points of the canopy gaps.

based on shape, texture, and color criteria. The algorithm was designed to handle high-resolution images efficiently, which is why we chose to use this algorithm due to very high-resolution images from the UAV.

To maximize the results, we used various iterations; we found the parameters that resulted in the best segmentation for detecting canopy gaps. We used a Scale Parameter of 200, a Shape of 0.1, and a Compactness of 0.5.
After the segmentation process was finished, the OBIA classification was done using the classification tool. The ground truthing points used for the classification were divided for classification (80%) and validation (20%). The classification points were chosen randomly. We selected features for the classification process by choosing the segmented objects that directly overlap the ground truthing points. After that, we did an accuracy assessment to see if classification was in detecting gaps. All of the above processes were completed in eCognition Developer 64.

2.6 Accuracy Assessment

The results of the OBIA classification from the segmentation will be assessed for accuracy. This is done to test the accuracy of a classified map versus the actual conditions in the field. The overall accuracy of a classified image is compared to how many features (polygons) exist between the actual conditions; the actual conditions are usually in the form of ground truth data. The producer's accuracy is to measure how well a land cover/object that is mapped can be classified. User's accuracy measures the likelihood of a classified polygon to its location in the real world.

2.7 Accurate Area Calculation without Gap

Using the following segmentation and OBIA classification, we could then create a map to see the mangrove species distribution and the detected canopy gaps. Besides that, we then dissolve the whole area of the segmentation to calculate the total area of each class. This process was done in QGIS using the field calculator's area syntax. The calculated area will be the same as the corresponding Coordinate System Referenced used, which, in our case, we used a Universal Transverse Mercator (UTM); the resulting area will be in m^2. We hypothesized that to calculate a more accurate mangrove area the total of the mangrove minus the canopy gaps area.

3. Results and Discussion

3.1 Distribution of Mangrove Species

After performing segmentation and OBIA, the results can be seen in Figure 5. We found two mangrove species in the field: *Rhizophora Mucronata* (RM) and *Avicennia sp*. (AV). This corresponds to a study done in the same area by Larekeng et al. (2024), in which they found three species of mangrove which are the following *Rhizopora apiculata*, *Avicennia sp, and Rhizopora mucronata*. For *R. Apiculata*, we did not find any of the individuals due to its distribution being outside our study area. From our ground-truthing points, we identified a total of 65 points. We found AV, 29 points, RA, and 4 points in which there were mixed AV and RA.

The distribution of mangrove species by zonation is determined by their suitability to grow in a specific area (substrate). Mangrove zonation can also be influenced by other topographic contours that form vegetation patterns (Tomlinson PB, 1994).

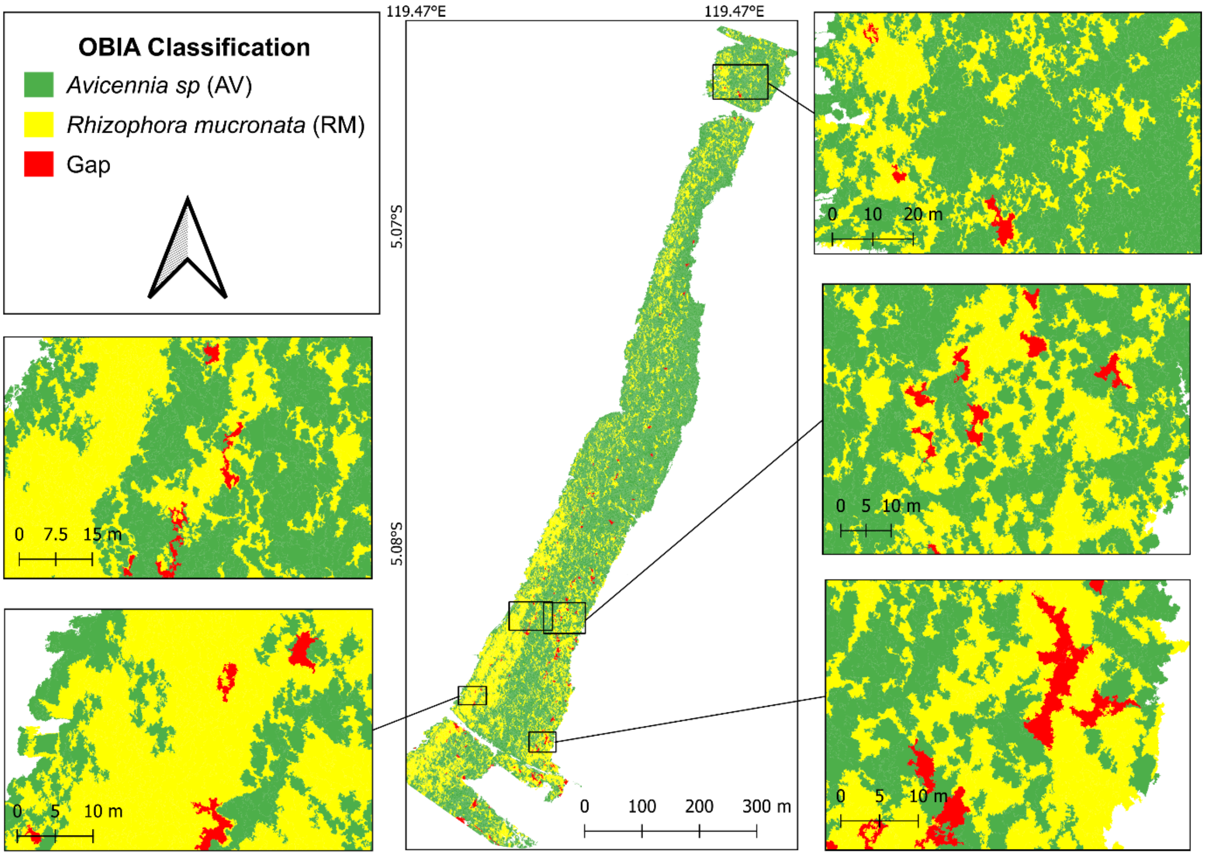

Figure 4. Distribution of AV, RM and Canopy Gap classes after OBIA classification in our study area.

For our research, we decided to create our zonation/fringes by the distance to the sea or to land. So, we created three zones which we created: seaward, landward, and interior.

This research has shown that the distribution of mangrove species zones is varied. In seaward zones, only RM can be found, in interior areas, a mix of RM and AV, and for landward, AV is dominantly present with rarely showing RM. For seaward zones, RM thrives in areas that experience tidal flooding (high and low tide). This results in an area of high salinity and low oxygen. RA's stilt roots help to anchor in soft sediments where it can withstand the currents (Matthijs et al., 1999). In contrast, AVs are mostly found in landward zones where tides rarely reach. Thus, creating areas where salinity is low, results in rich and stable oxygen, perfect for AV to thrive.

3.2 Challenges of Mapping Mangrove Canopy Gaps using UAV-RGB

There is still limited research on mapping mangrove canopy gaps by remote sensing approach and even less is being done that uses UAV. To our understanding and preliminary literature, research shows that there are, in total, only three studies that have researched on mapping canopy gaps in mangrove forests. Two of these were used airborne LiDAR done by (Zhang, 2008; Zhang et al., 2008), and one research that used VHR (Very High Resolution) satellite images (Turner et al., 2012).

Our challenge was that the UAV we used only used an RGB sensor, which could not explicitly detect gaps in mangroves unlike LiDAR or multispectral sensors. LiDAR provides vertical and horizontal information about a forest's area in a high resolution (Gaulton & Malthus, 2010). The satellite images that was used in Taureau et al. research were WorldView-3 and -4 images, consisting of a multispectral sensor VNIR (Visible Near-Infrared, 400-1000 nm) range and 0.3 m panchromatic channel. Using the pan-sharpening algorithm to create a higher resolution image, the resulting images were 0.3 m (Taureau et al., 2019). It was challenging to detect canopy gaps because we only used a camera with an RGB sensor.

Our UAV images had a GSD (Ground Sample Distance) of 2.8 cm; when compared to detected gaps in the study area, it was not as large compared to other research that has been done (Lassalle & de Souza Filho, 2022). Our findings of the gap area (m^2) by OBIA classification were 86.27 m^2. To our understanding, no research has been done of mapping mangrove canopy gaps in Indonesia. The closest territory we found that studied canopy gaps in detail was done by Amir (2012) in Malaysia; the gap size ranged from 390 m^2 to 5112 m^2**.**

In our case, for us to accurately detect canopy gaps, it had to be big enough, no other trees to cover the gap, and it had to have the right light conditions (solar azimuth angle). The size of the gap was important because small gaps that are detected in reality can be just height differences between tree species/individuals. Duke (2001), explains that in areas where mangroves are mixed

Avicennia is more favored due to its fast growth from damaged stems and vegetative growth. *Rhizophora* trees also tend not to focus on vegetative growth. Our observation in the field also yields similar results, which is one reason why there are more canopy gaps near the landward fringe compared to the seaward fringe.

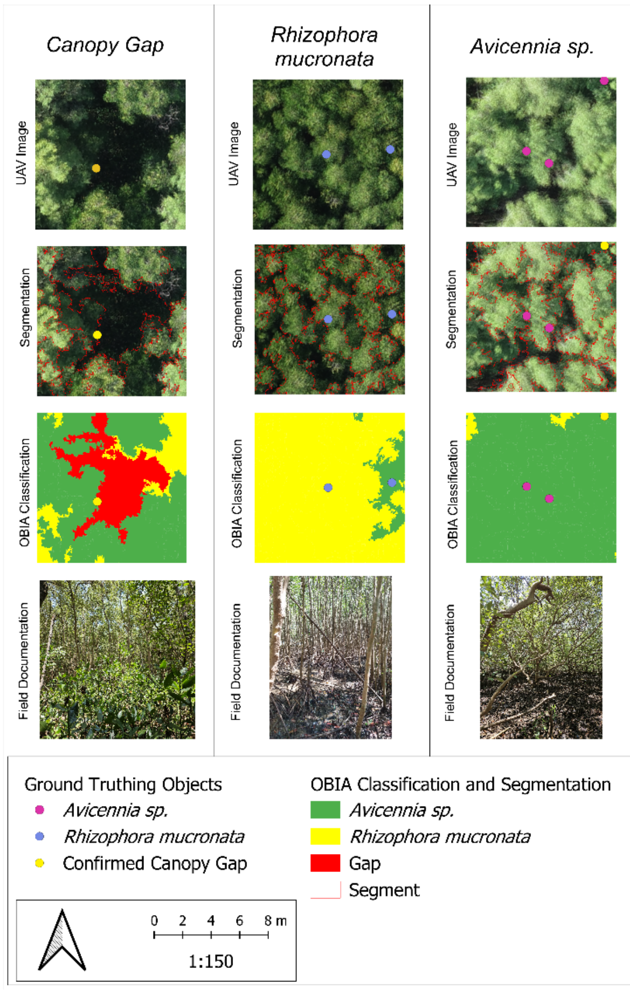

Figure 5. From UAV imagery to OBIA classification with the corresponding field documentation.

3.3 Causes of Canopy Gaps

We also studied the causes of gaps and their surrounding conditions. The cause of gaps varied, but out of 18 confirmed gaps, seven were due to old age, two were natural causes, six were due to lightning strikes, and three were unknown. The unknown causes we couldn't identify them because we were not sure of the exact causes of the gaps. The 11 gaps we identified landward in the southern side were mainly caused by lightning strikes and old age. Since we couldn't identify the exact causes of each gap, we suggest that the most likely cause is a lightning strike and old age. It is not apparent due to the tree that caused the gap creation mainly starting to decompose or already decomposed. Figure 7. shows some examples of the field of gap-creation trees that were in the process of decomposing and already decomposed.

The cause of gaps that we identified as lightning strikes was that the tree burnt and was still standing with most of its branches intact. Trees that have been struck by lightning are usually distinguished if they are scorched, stripped of their leaves, severed horizontally, sometimes a bark is stripped, and its crown may also be withered (Latham & Williams, 2001). We cannot mention the severity of the damage caused by a lightning strike on a tree explicitly due to the small amount of research done on factors that can affect where lightning strikes on trees.

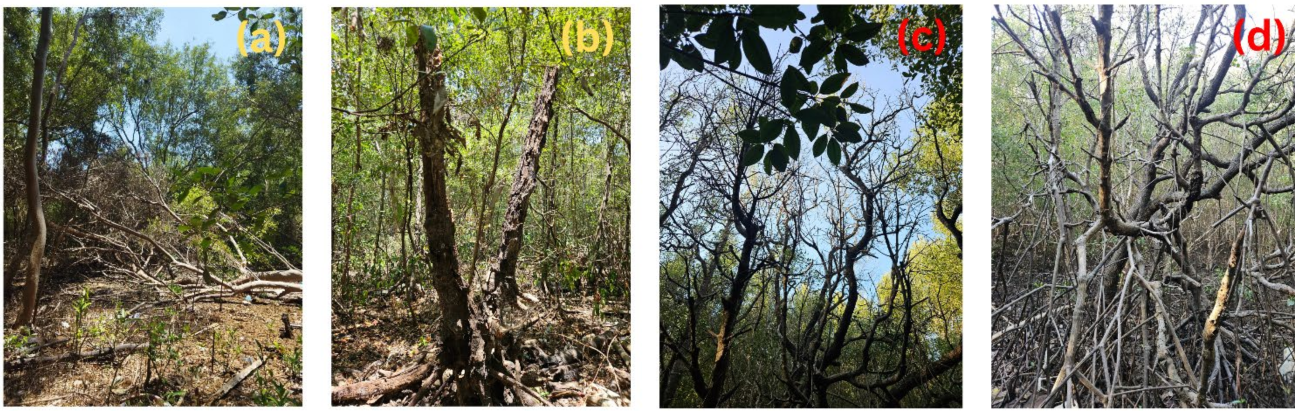

Figure 6. Various causes of canopy gaps that is be seen. Only in picture (a) can we determine precisely the causes which is fallen tree/s. (a) fallen tree, (b) lightning strike, (c, d) one very large RM tree that has created a large gap, the colour and medium-large cracks may indicate lightning strike.

Yanoviak et al. (2020) mention that more research needs to be done on how lighting strikes affect different forests of different ages, species/genus composition, structures, and the lightning's characteristics (e.g., intensity, duration, polarity).

Sherman et al. (2000) researched identifying gaps through aerial photography and found that gaps caused by lightning were easily distinguishable due to the uniformity of the canopy structure. The research that was done in the Dominican Republic consisted of various classes which included *Rhizophora*, *Languncularia*, *Rhizophora-Laguncularia* mix, and *Rhizophora-Laguncularia-Avicennia* mix. Sherman et al. explained for *Avicennia* dominated areas, it was hard to differentiate between gaps and the varied canopy heights of multiple species *(Avicennia* and *Rhizophora*).

Our research faced the same problem: areas of RA were hard to differentiate between canopy heights and canopy gaps. It was still hard to differentiate for gaps that were old or considered gap growth stage due to the stands being similar to or the same height as the surrounding canopy heights. We can see many small gaps in the UAV imagery, but in reality, it is trees with small/medium height differences. We experienced the same hurdle in which there were areas with mixed species, so we were categorized into another class, *Rhizophora-Avicennia* (RA). Landward areas had a mix of RA and AV dominant classes. Only RM were found in interior areas, seaward fringes were dominated by RM and RA.

In Figure 5 we can see that gaps are mostly found landward and interior fringe where the present species are a mix of RA and AV. The gaps where the trees were still standing or either fallen down, were very tall trees which in most likely were caused burnt due to lightning strikes.

3.4 Accuracy Assessment

To test and validate our OBIA classification of our three classes which are RM, AV, and canopy gaps; we used a error matrix to calculate the user accuracy, producer accuracy, and overall accuracy. The overall accuracy assessment shows that the model identified the three classes well, but producer and user accuracy results suggest that some classes were better than others.

RM had a high classification accuracy with producer’s accuracy of 88.89% and a users accuracy of 80%. The results explains that most segmented objects of the OBIA classification was correctly identified. AV in the other had a producers accuracy of 83.33% and a user’s accuracy of 76.92%. The lower accuracy may be due to the similar spectral resolution and also may be in fact due to the areas where mixed species in prevalent. Canopy gaps were the most challenging due to the classify, this is reflected on the producer’s accuracy of 70.00% and users accuracy of 87.5%. The high omission (30%) shows that the canopy gaps indicates that are misclassified either AV or RM.

Class	RM	AV	Gap	P. Sum	**P. Accuracy (%)**
RM	**8**	0	1	9	88.88
AV.	2	**10**	0	12	83.33
Gap	0	3	**7**	10	70
U. Sum	10	13	8		
U. Accuracy (%)	80	76.92	87.5		
Overall Accuracy (%)					**80.65**

Table 2. Accuracy assessment results

There are a few factors that must be taken that caused misclassification. Spectral similarity which must be taken because of the segmentation algorithm where one of its parameters that it priorities is spectral signature. Mixed classes in the field as mentioned in this research shows in the field some canopy are identified AV but in reality its RM due to the overlapping of canopies. To increase the validation of this accuracy assessment, a required step should be to increase the ground truthing points.

3.5 Proposed Formula for Calculating Accurate Mangrove Area

After segmentation, the OBIA classification resulted in three classes: RM, AV, and canopy gaps. These three classes, when dissolved, each resulted in an area of AV 12.56 ha, RM 5.486 ha, and Canopy Gap 0.23 ha. Conventional methods for calculating mangrove area is to calculate the total area of the mangrove area without considering the canopy gaps. The formula is written as below (1):

$$A_{area\ of\ a\ mangrove} = A_{MS1} + A_{MS2} + \cdots, A_n, \qquad (1)$$

Where A_{MS1} = total area of mangrove species 1
A_{MS2} = total area of mangrove species 2
A_n = total area of other mangrove species

Using the standard method (formula 1) to calculate the area of a mangrove, results in an area of 18.27 ha.

Our proposed formula is a simple equation that takes account of the canopy gap area:

$$A_{accurate\ area\ of\ a\ mangrove} = A_2 - A_1, \quad (2)$$

where A_2 = total area of the mangrove with canopy gaps
A_1 = total area of canopy gaps

To our understanding, no research has a more detailed and accurate way to calculate the mangrove area. Using the second formula we proposed, the more accurate area of mangroves is 17.81 ha. There is a difference of 0.46 ha.

Our findings are still the very bare minimum, from the tools we have and methods we used to gather the data. More specifically, there should be more research on how to identify canopy gaps more accurately and its area. In our research, we only used one segmentation algorithm, which is multiresolution segmentation. With the availability and more polished algorithms based on deep learning, this is recommended for further research on canopy gaps; one example done is by (Lassalle & de Souza Filho, 2022). This algorithm that we used can be considered old, but with our findings we found that it still can be used.

For the tools we used, there should be more iterations on the UAV acquisition, such as the flight mission parameters and the flight time. Such examples that can be done is to compare the results of the same flight mission parameters but different flight times; this may shed new light on the ideal parameters for UAV imagery acquisition for canopy gaps.

Canopy gaps are still not a well researched phenomenon. Even though (Amir, 2012; Duke, 2001) research has shed new light on canopy gaps, there is still no new research on identifying the cause of canopy gaps, how they affect the surrounding trees, and how they also affect other biotas and fauna in the mangrove area. We hope with this research, more people will research mangroves in tropical and sub-tropical areas, as they are two completely different environments.

4. Conclusion

There are still many flaws in our methodologies and many shortcomings, such as locating gaps, identifying the cause of the gaps, not calculating the actual area of the canopy gap in the field, using different sensors to help locate gaps, and many more. With the new proposed formula, there should be more research to accurately calculate an area of canopy gap and newer methods to calculate it more accurately. Hopefully, these findings can open a new perspective on calculating a mangrove area, especially in areas prone to canopy gaps that are anthropogenic or natural causes. Calculating an accurate area of mangroves and calculating canopy gaps is important for rehabilitation and monitoring purposes.

Another note is that in our literature research, most, if not all, research that has been done on mangrove canopy gaps is in areas where mostly single species thrive, not mixed species. This creates a challenge in our study areas as it is also harder to map the accurate species distribution due to mixed species intertwining and overlapping each other. One of our key findings was that using a UAV with an RGB sensor can detect different

5. Acknowledgments

We would like to thank Much. Faizal Rachman, S.Kel for accompanying us in the field for collecting the data. We would also like to thank Dr. A. Aldrie Amir, who gave us additional information on canopy gaps. Thank you to the Ministry of Higher Education, Science, and Technology (Kemdiktisaintek) through the program eASIA with contract number: 015/E5/PG.02.00/PRPB BATCH 2/2024.

References

Almeida de Oliveira, P., Conti, L. A., Nascimento Neto, F. C., Barcellos, R. L., & Cunha-Lignon, M. (2024). Mangrove individual tree detection based on the uncrewed aerial vehicle multispectral imagery. *Remote Sensing Applications: Society and Environment*, *33*, 101100. https://doi.org/10.1016/J.RSASE.2023.101100

Amir, A. A. (2012). Canopy gaps and the natural regeneration of Matang mangroves. *Forest Ecology and Management*, *269*, 60–67. https://doi.org/10.1016/J.FORECO.2011.12.040

Amir, A. A., Duke, N. C., Amir, A., & Duke, N. (2009). *A forever young ecosystem: light gap creation and turnover of subtropical mangrove forests in Moreton Bay, southeast Queensland, Australia*. https://www.researchgate.net/publication/47806885

Baatz, M., & Schäpe, A. (2000). *Multiresolution Segmentation : an optimization approach for high quality multi-scale image segmentation*. https://api.semanticscholar.org/CorpusID:16808522

Cao, J., Xu, X., Zhuo, L., & Liu, K. (2023). Investigating mangrove canopy phenology in coastal areas of China using time series Sentinel-1/2 images. *Ecological Indicators*, *154*, 110815. https://doi.org/https://doi.org/10.1016/j.ecolind.2023.110815

DJI. (2021). *Phantom 4 Pro V2.O Quick Start Guide*. http://www.dji.com/phantom-4-pro-v2

Doukari, M., Batsaris, M., Papakonstantinou, A., & Topouzelis, K. (2019). A protocol for aerial survey in coastal areas using UAS. *Remote Sensing*, *11*(16). https://doi.org/10.3390/rs11161913

Duke, N. C. (2001). Gap creation and regenerative processes driving diversity and structure of mangrove ecosystems. *Article in Wetlands Ecology and Management*. https://doi.org/10.1023/A:1011121109886

Fu, B., He, X., Yao, H., Liang, Y., Deng, T., He, H., Fan, D., Lan, G., & He, W. (2022). Comparison of RFE-DL and stacking ensemble learning algorithms for classifying mangrove species on UAV multispectral images. *International Journal of Applied Earth Observation and Geoinformation*, *112*, 102890. https://doi.org/10.1016/J.JAG.2022.102890

Gaulton, R., & Malthus, T. J. (2010). LiDAR mapping of canopy gaps in continuous cover forests: A comparison of canopy height model and point cloud based techniques. *International Journal of Remote Sensing*, *31*(5), 1193–1211. https://doi.org/10.1080/01431160903380565

Imai, N., Takyu, M., Nakamura, Y., & Nakamura, T. (2006). Gap formation and regeneration of tropical mangrove forests in Ranong, Thailand. *Plant Ecology*, *186*(1), 37–46. https://doi.org/10.1007/s11258-006-9110-y

(IPCC), I. P. on C. C. (2022). *Climate Change 2022 – Impacts, Adaptation and Vulnerability: Working Group II Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press. https://doi.org/DOI: 10.1017/9781009325844

K, A., Parveen K, H., V K, S., P, B., Muhammed, J., & Augustine, A. (2024). Mangroves in environmental engineering: Harnessing the multifunctional potential of nature's coastal architects for sustainable ecosystem management. *Results in Engineering*, *21*. https://doi.org/10.1016/j.rineng.2024.101765

Kameyama, S., & Sugiura, K. (2021). Effects of Differences in Structure from Motion Software on Image Processing of Unmanned Aerial Vehicle Photography and Estimation of Crown Area and Tree Height in Forests. *Remote Sensing*, *13*(4), 626. https://doi.org/10.3390/rs13040626

Kauffman, J. B., Adame, M. F., Arifanti, V. B., Schile-Beers, L. M., Bernardino, A. F., Bhomia, R. K., Donato, D. C., Feller, I. C., Ferreira, T. O., Jesus Garcia, M. del C., MacKenzie, R. A., Megonigal, J. P., Murdiyarso, D., Simpson, L., & Hernández Trejo, H. (2020). Total ecosystem carbon stocks of mangroves across broad global environmental and physical gradients. *Ecological Monographs*, *90*(2). https://doi.org/10.1002/ecm.1405

Larekeng, S. H., Nursaputra, M., Mappiasse, M. F., Ishak, S., Basyuni, M., Sumarga, E., Arifanti, V. B., Aznawi, A. A., Rahmila, Y. I., Yulianti, M., Rahmania, R., Mubaraq, A., Salmo, S. G., 10, I., Ali, H. M., & Yeny, I. (2024). Global Journal of Environmental Science and Management Estimation of mangrove carbon stocks using unmanned aerial vehicle over coastal vegetation. *Global J. Environ. Sci. Manage*, *10*(3), 39. https://doi.org/10.22034/gjesm.2024.03

Lassalle, G., & de Souza Filho, C. R. (2022). Tracking canopy gaps in mangroves remotely using deep learning. *Remote Sensing in Ecology and Conservation*, *8*(6), 890–903. https://doi.org/10.1002/rse2.289

Latham, D., & Williams, E. (2001). Lightning and Forest Fires. *Forest Fires*, 375–418. https://doi.org/10.1016/B978-012386660-8/50013-1

Li, S., Zhu, Z., Deng, W., Zhu, Q., Xu, Z., Peng, B., Guo, F., Zhang, Y., & Yang, Z. (2024). Estimation of aboveground biomass of different vegetation types in mangrove forests based on UAV remote sensing. *Sustainable Horizons*, *11*, 100100. https://doi.org/10.1016/J.HORIZ.2024.100100

Lim, H. S., Lee, Y., Lin, M. H., & Chia, W. C. (2024). Mangrove species detection using YOLOv5 with RGB imagery from consumer unmanned aerial vehicles (UAVs). *The Egyptian Journal of Remote Sensing and Space Sciences*, *27*(4), 645–655. https://doi.org/10.1016/J.EJRS.2024.08.005

Matthijs, S., Tack, J., van Speybroeck, D., & Koedam, N. (1999). Mangrove species zonation and soil redox state, sulphide concentration and salinity in Gazi Bay (Kenya), a preliminary study. *Mangroves and Salt Marshes*, *3*(4), 243–249. https://doi.org/10.1023/A:1009971023277

Ngo, D. T. (2024). Mapping tree species of wetlands using multispectral images of UAVs and machine learning: A case study of the Dong Rui Commune. *Heliyon*, *10*(15), e35159. https://doi.org/10.1016/J.HELIYON.2024.E35159

Pham, T. D., Yokoya, N., Bui, D. T., Yoshino, K., & Friess, D. A. (2019). Remote sensing approaches for monitoring mangrove species, structure, and biomass: Opportunities and challenges. In *Remote Sensing* (Vol. 11, Issue 3). MDPI AG. https://doi.org/10.3390/rs11030230

Pix4D. (2025). *Processing Options Default Templates - PIX4Dmapper*. Https://Support.Pix4d.Com/Hc/En-Us/Articles/205319155.

Runkle, J. R. (1985). Disturbance Regimes in Temperate Forests. *The Ecology of Natural Disturbance and Patch Dynamics*, 17–33. https://doi.org/10.1016/B978-0-08-050495-7.50007-7

Sherman, R. E., Fahey, T. J., & Battles, J. J. (2000). Small-scale disturbance and regeneration dynamics in a neotropical mangrove forest. *Journal of Ecology*, *88*(1), 165–178. https://doi.org/https://doi.org/10.1046/j.1365-2745.2000.00439.x

Suhardi, R. M., Rahardi, W., Shih, H. C., Mantiquilla, J. A., Wu, Y. H., Shiao, M. S., & Chiang, Y. C. (2024). A review of the mangrove ecosystem in Indonesia: Biodiversity, conservation, and challenges in sustainable management. *Ecological Genetics and Genomics*, *32*, 100282. https://doi.org/10.1016/J.EGG.2024.100282

Swayze, N. C., & Tinkham, W. T. (2022). Application of unmanned aerial system structure from motion point cloud detected tree heights and stem diameters to model missing stem diameters. *MethodsX*, *9*, 101729. https://doi.org/10.1016/J.MEX.2022.101729

Taureau, F., Robin, M., Proisy, C., Fromard, F., Imbert, D., & Debaine, F. (2019). Mapping the mangrove forest canopy using spectral unmixing of very high spatial resolution satellite images. *Remote Sensing*, *11*(3). https://doi.org/10.3390/rs11030367

Tomlinson PB. (1994). *The Botany of Mangroves.* (1st Edition). Cambridge Press.

Turner, D., Lucieer, A., & Watson, C. (2012). An automated technique for generating georectified mosaics from ultra-high resolution Unmanned Aerial Vehicle (UAV) imagery, based on Structure from Motion (SFM) point clouds. *Remote Sensing*, *4*(5), 1392–1410. https://doi.org/10.3390/rs4051392

Whitmore, T. C. (1989a). Canopy Gaps and the Two Major Groups of Forest Trees. *Ecology*, *70*(3), 536–538. https://doi.org/https://doi.org/10.2307/1940195

Whitmore, T. C. (1989b). Canopy Gaps and the Two Major Groups of Forest Trees. *Ecology*, *70*(3), 536–538. https://doi.org/10.2307/1940195

Yang, Y., Meng, Z., Zu, J., Cai, W., Wang, J., Su, H., & Yang, J. (2024). Fine-Scale Mangrove Species Classification Based on UAV Multispectral and Hyperspectral Remote Sensing Using Machine Learning. *Remote Sensing*, *16*(16). https://doi.org/10.3390/rs16163093

Yanoviak, S. P., Gora, E. M., Bitzer, P. M., Burchfield, J. C., Muller-Landau, H. C., Detto, M., Paton, S., & Hubbell, S. P. (2020). Lightning is a major cause of large tree mortality in a lowland neotropical forest. *New Phytologist*, *225*(5), 1936–1944. https://doi.org/https://doi.org/10.1111/nph.16260

Yin, D., Wang, L., Lu, Y., & Shi, C. (2024). Mangrove tree height growth monitoring from multi-temporal UAV-LiDAR. *Remote Sensing of Environment*, *303*, 114002. https://doi.org/10.1016/J.RSE.2024.114002

Zhang, K. (2008). Identification of gaps in mangrove forests with airborne LIDAR. *Remote Sensing of Environment*, *112*(5), 2309–2325. https://doi.org/10.1016/J.RSE.2007.10.003

Zhang, K., Simard, M., Ross, M., Rivera-Monroy, V. H., Houle, P., Ruiz, P., Twilley, R. R., & Whelan, K. R. T. (2008). Airborne Laser Scanning Quantification of Disturbances from Hurricanes and Lightning Strikes to Mangrove Forests in Everglades National Park, USA. *Sensors*, *8*, 2262–2292. www.mdpi.org/sensors

Zimudzi, E., Sanders, I., Rollings, N., & Omlin, C. W. (2021). Remote sensing of mangroves using unmanned aerial vehicles: current state and future directions. In *Journal of Spatial Science* (Vol. 66, Issue 2, pp. 195–212). Mapping Sciences Institute Australia. https://doi.org/10.1080/14498596.2019.1627252