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Classification of Mangrove Vegetation Structure using Airborne LiDAR in Ratai Bay, Lampung Province, Indonesia

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Abstract

Mapping and inventory of the distribution and composition of mangrove vegetation structures are crucial in managing mangrove ecosystems. The availability of airborne LiDAR remote sensing technology provides capability of mapping vegetation structures in three dimensions. It provides an alternative data source for mapping and inventory of the distribution of mangrove ecosystems. This study aims to test the ability of airborne LiDAR data to classify mangrove vegetation structures conducted in Ratai Bay, Pesawaran District, Lampung Province. The classification system applied integrates structure attributes of lifeforms, canopy height, and canopy cover percentage. Airborne LiDAR data are derived into canopy height models (CHM) and canopy cover percentage models, then grouped by examining statistics and the zonation distribution of mangroves in the study area. The results of this study show that airborne LiDAR data are able to map vegetation structures accurately. The canopy height model derived using a pit-free algorithm can represent the maximum tree height with an error range of 3.17 meters and 82.3-88.6% accuracy. On the other hand, the canopy cover percentage model using LiDAR Fraction Cover (LFC) tends to be overestimate, with an error range of 16.6% and an accuracy of 79.6-94.7%. Meanwhile, the classification results of vegetation structures show an overall accuracy of 77%.

1. Introduction

Mangrove is a type of vegetation characterized by its ability to grow in tidal areas, and its presence plays an important role in human life in coastal regions (Murray et al., 2019). Well-established mangroves can provide various environmental services in coastal areas. For example, as carbon storage, protecting coastlines, serving as habitats for marine biota, and potentially becoming tourist attractions that provide significant economic benefits to coastal communities (Alongi, 2009; Duke et al., 1998; Saenger, 2002). On the other hand, Indonesia is an archipelagic country with the largest mangrove ecosystem in the world (FAO, 2007; Spalding et al., 1997). In 2021, the area of mangrove forests in Indonesia was estimated to be around 3.31 million hectares (Ministry of Environment and Forestry, 2021). Therefore, information regarding the distribution and condition of mangroves is crucial to support various sustainable mangrove management policies in Indonesia.

A functional relationship between components in the mangrove ecosystem results in a complex forest structure with tall trees and a dense layer of vegetation vertically and horizontally (Ehbrecht et al., 2021). A mapping classification scheme has been developed to facilitate understanding the distribution of mangrove vegetation structures. It groups mangroves based on their structural similarities. Specht (1970, in Saenger,

2002) developed a classification scheme that groups vegetation structures based on lifeforms attributes, tree height, and leaf coverage. Kamal et al. (2015) also conducted a similar classification model, where vegetation composition and canopy coverage were important parameters in classifying mangrove zones. Even the classification scheme of vegetation structures can be combined with species zoning to map more detailed typologies of mangrove vegetation (Almeida et al., 2020).

The utilization of remote sensing data provides advantages in vegetation studies, particularly in presenting spatial information and conducting research at local to global scales (Xie et al., 2008). One remote sensing technology developed for vegetation studies is Light Detection and Ranging (LiDAR), which can represent forest vegetation structure attributes in three dimensions (Bakx et al., 2019; Coops et al., 2021; Lefsky et al., 2002). LiDAR data can be extracted into vegetation structure information at the community level, and in some cases, detailed studies can be conducted at the individual level (Bakx et al., 2019; Yin & Wang, 2019).

Based on previous research, the most frequently derived vegetation structure parameters from LiDAR data include volume, height, surface biomass, basal area, canopy cover, and height complexity, providing accurate results (Almeida et al., 2019; Armston, 2009; Bakx et al., 2019; Coops et al., 2021; Guo et al., 2017; Hopkinson & Chasmer, 2009; Khosravipour et al., 2014; Lefsky et al., 2002; Mahoney et al., 2018; Yin & Wang, 2019). Vegetation structure attributes derived from LiDAR can be used as variables in classifying mangrove species zonation, enabling an accurate inventory of mangrove ecosystem conditions (Barenblitt et al., 2023; Kamal et al., 2015; Li et al., 2019, 2021; Ou et al., 2023; Wang et al., 2018, 2022; Zhang et al., 2006). However, there haven't been many studies examining the utilization of LiDAR data for the classification of mangrove vegetation structures. Mangrove zonation, nevertheless, is not only associated with species differences but also with the diversity of vegetation structures (Lucas et al., 2017).

Despite its potential for data utilization in vegetation studies, there have been relatively few studies on mangrove mapping using LiDAR data in Indonesia. This study aims to investigate the classification of mangrove vegetation structures using airborne LiDAR data in the mangrove forest of Ratai Bay, Pasawaran District, Lampung Province. The main focus of this research is to test the ability of airborne LiDAR data to classify the structure of mangrove vegetation in the study area. An accuracy assessment will be conducted on vegetation structure variables extracted from LiDAR data and their classification results.

The choice of research location was based on the fact that the mangrove forest in Ratai Bay is part of the mangrove ecosystem in Lampung Bay which grows naturally and has a high variation in species composition and vegetation structure (Dwiputra & Mustofa, 2021; Juniansah et al., 2018; Nabilah et al., 2021; Wijaya et al., 2023).

2. Data and Methods

2.1. *Study Site*

The study site is located in Ratai Bay, Pesawaran Regency, Lampung Province, situated between 105° 09' 40" - 105° 10' 55" East and 05° 34' 45" - 05° 36' 04" South (Figure 1). The research site is a natural habitat of mangroves which is located at the estuary of the Ratai River. It is a relatively protected area of Lampung Bay that making it an excellent location for this type of study. There have been few studies on the distribution and composition of mangroves in this location. Research on mangroves in Teluk Ratai was conducted by Juniansah et al. (2018), indicating that this location has high potential for primary productivity of mangrove vegetation, as demonstrated by its high Leaf Area Index (LAI) values. Additionally, Wijaya et al. (2023) also mention that Teluk Ratai has a high biodiversity of mangrove species. The research site is also part of the mangrove conservation zone outlined in the coastal and small islands zone plan issued by the Province of Lampung. Therefore, an inventory of its structure and vegetation composition are crucial to support the management and conservation of mangroves.

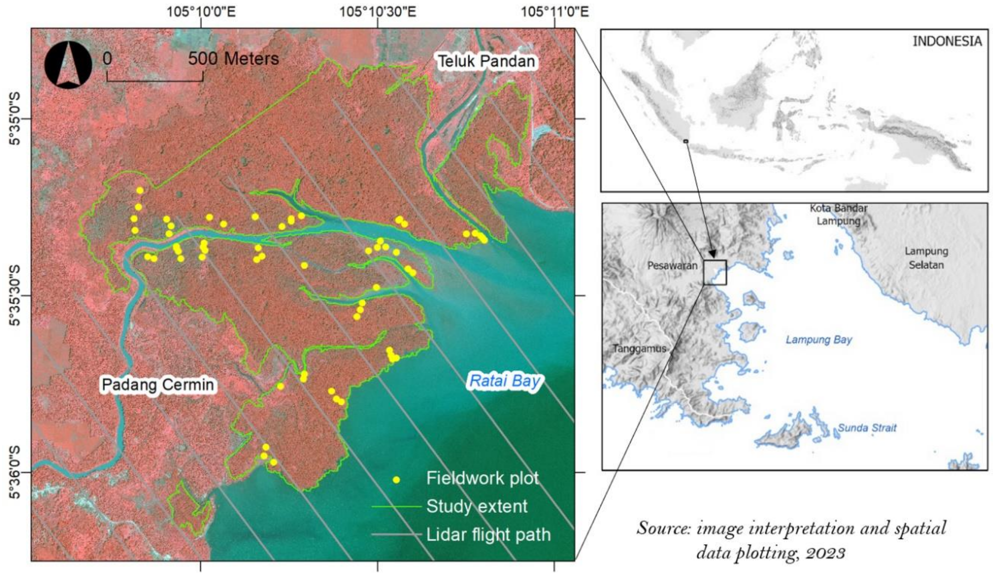

Figure 1. Study site in Ratai Bay and the Fieldwork Plots Distribution; the Background Image is a Pan-Sharpened Standard False Color Pléiades Image Acquired in 2020.

2.2. Research Data

The primary data used in this study is airborne LiDAR data. Airborne LiDAR is a laser system installed on an aircraft that provides three-dimensional position information of vegetation objects (Coops et al., 2021). The laser pulses emitted by the LiDAR sensor can penetrate through the gaps between leaves in the canopy to the ground surface, enabling the LiDAR data to produce several attributes of vegetation structure, such as mean canopy height, canopy cover percentage, high canopy complexity, basal area, and stand volume (Coops et al., 2021; Luther et al., 2019; Mahoney et al., 2018). The specifications of the airborne LiDAR data used in this study can be seen in Table 1. In addition to using airborne LiDAR data, this study employs the Indonesian National Mangrove Map to discriminate between mangrove and non-mangrove vegetation areas. The airborne LiDAR data used in this study were acquired in December 2020 to model the coastline and were not specifically intended for mapping mangroves. Therefore, there is mangrove vegetation in the study area that is not covered by the airborne LiDAR data. The extent of the mangrove area covered by the airborne LiDAR data can be seen in Figure 1.

Table 1. Data Source and Specification

No	Data Type	Data Source	Specification
1	Airborne LiDAR	Geospatial Information Agency	20 points per square meter, acquired in December 2020
2	Indonesian National Mangrove Map	Ministry of Environment and Forestry of the Republic of Indonesia	The map scale is 1: 25,000
3	Field survey data	Ground check data	Data acquired in October 2022

Source: Research Data Specification, 2023

2.3. Fieldwork Data

Fieldwork was conducted to collect data about mangrove forest characteristics, tree height, canopy cover percentage, and dominant species. The fieldwork plot distribution is presented in Figure 1, and the field plot data scheme implemented in this study can be seen in Figure 2a. We conducted visual observations for lifeform and tree height measurements for all identified mangrove vegetation within 10 x 10-meter plots. The hemispherical photography procedures were carried out using a camera lens with a 180-degree field of view that could represent the size of the 10 x 10-meter plots (Figure 2b). The photo capture location was precisely

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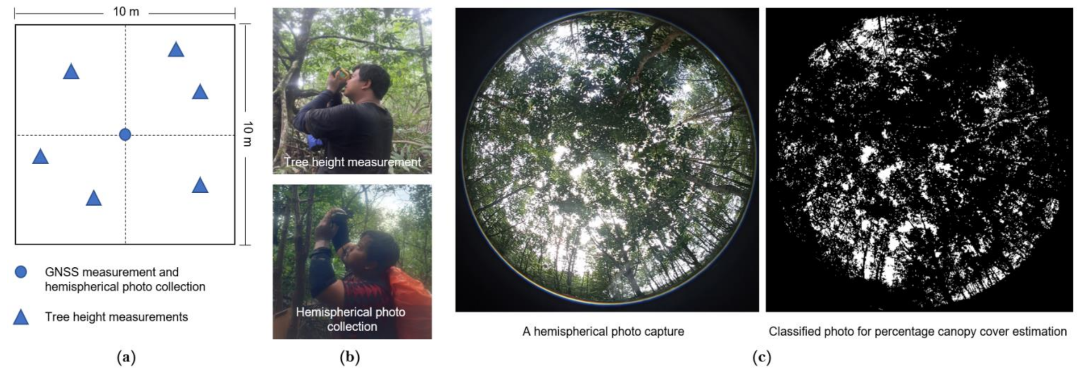
at the midpoint of the sample plot or the same as the Global Navigation Satellite System (GNSS) receiver measurement location. It is intended to determine the photo's absolute coordinates and ensure that the coverage could represent the canopy closure condition throughout the plot. The canopy closure percentage was estimated on hemispherical photos by examining the ratio of light gap fraction to leaves throughout the photo coverage (Chianucci, 2019; Jennings et al., 1999; Korhonen et al., 2006) (Figure 2c). The canopy cover percentage estimation was carried out with the help of the Gap Light Analyzer software (Frazer et al., 1999).

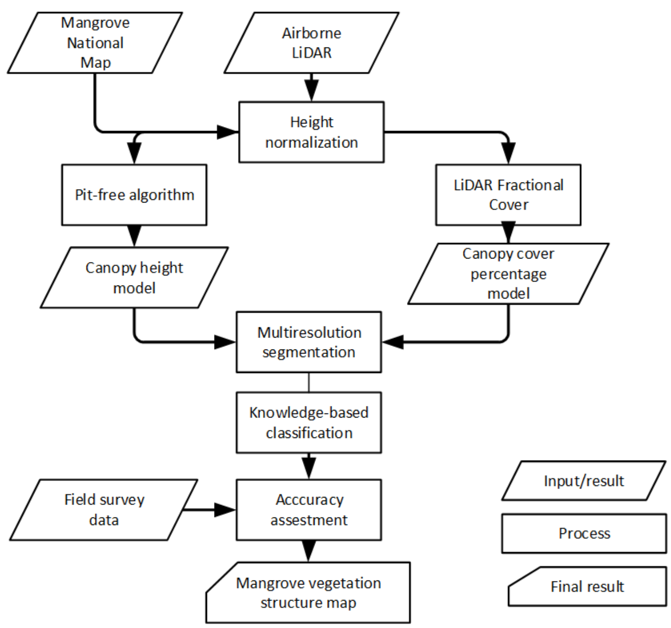


Source: Field Documentation, 2023

Figure 2. Fieldwork Activity: (a) Field Plot Data Scheme, (b) Documentation of Tree Height and Hemispherical photo Collection, (c) hemispherical Photo Result and canopy Cover Percentage Estimation.

2.4. Mangrove Vegetation Structure Mapping

Before analysis, the LiDAR point cloud data had to be processed through a height normalization for the z-value to represent the height of the tree canopy. It is because the z-value in the point cloud data was calculated based on the ellipsoid height reference, not the height of the ground beneath it (Poorazimy et al., 2022). In height normalization, the z-value of the point cloud will be subtract by the height value of the ground surface, which has been formed previously using a triangulated irregular network (TIN). Figure 3 shows the research flowchart conducted in this study.



Source: Research Component Identification, 2023

Figure 3. The Research Flow Chart Conducted in this Study.

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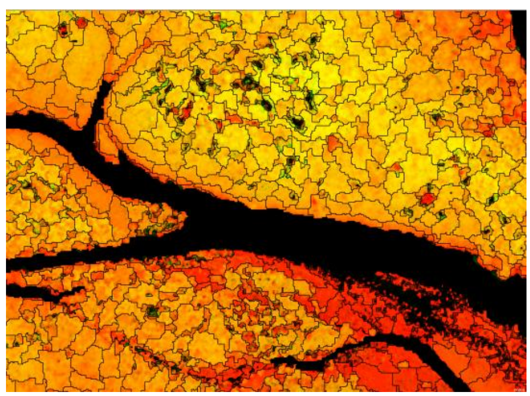
The canopy cover percentage was extracted using the LiDAR fractional cover (LFC) algorithm developed by (Armston, 2009). The LFC works by using the concept of gap fraction on the first return pulse of LiDAR data that hits vegetation objects. As shown in Eq (1), the number of first returns that hit vegetation canopies is compared to the total number of first returns that reach the ground surface on a specific grid unit area (Armston, 2009; Hopkinson & Chasmer, 2009). Considering the density of point cloud data, the grid size for the canopy cover percentage map was set at 2 x 2 meters.

$$LFC \;=\; \frac{\sum First\ Return\ Canopy/Non\ Ground}{\sum First\ Return} \ldots\ldots\ldots\ldots\ldots\ldots\ldots. (Eq.1)$$

The vegetation height parameter was extracted using the canopy height model (CHM) algorithm based on the pit-free method developed by Khosravipour et al. (2014). The pit-free algorithm works by finding the highest value of the first return and processing it layer by layer to avoid data holes in the resulting canopy height (Khosravipour et al., 2014; Arjasakusuma et al., 2020; Poorazimy et al., 2022). The grid size of the canopy height model was set to 2 x 2 meters, the same as the canopy percentage cover map. In further applications, the CHM generated from LiDAR data can be used to identify the canopy boundaries of each mangrove tree (Yin & Wang, 2019). After vegetation height parameters and canopy cover percentage extracted, both data were classified into a vegetation structure map using an object-based approach. The segmentation process was conducted using a multi-resolution algorithm to separate mangrove community zones in the study area. This algorithm was chosen because of its ability to divide object boundaries in high-spatial-resolution images based on scale, shape, and compactness parameters (Kamal et al., 2015; Kamal, Phinn, et al., 2016; Pasaribu et al., 2021). The segmentation parameter values were determined through several trials to ensure that the mangrove objects' homogeneity, based on height and canopy cover percentage values, could be separated. The resulting segmentation with parameter values of scale (11), shape (0.2), and compactness (0.6) can be seen in Figure 4.



Source: Image Analysis, 2023

Figure 4. An example of Segmentation Results of Airborne LiDAR Data.

The classification of vegetation structure was carried out using a knowledge-based classification system formed through a decision tree rule-set classification. The classification system used was based on the modified vegetation structure classification developed by Specth (1970, in Saenger (2002)). This classification system divides vegetation structure based on attributes of lifeform, height, and canopy cover percentage. In addition to species similarity, the equivalence of vegetation structure classes can form the mangrove zonation (Kamal et al., 2016).

2.5. Accuracy Assessment of the Mapping Results

An accuracy assessment was conducted to evaluate the quality of the vegetation structure classification map against the data from mangrove plot surveys in October 2022. The sample plot survey method used modified procedures from the National Indonesian Standard No. 7717-2020 on Mangrove Geospatial

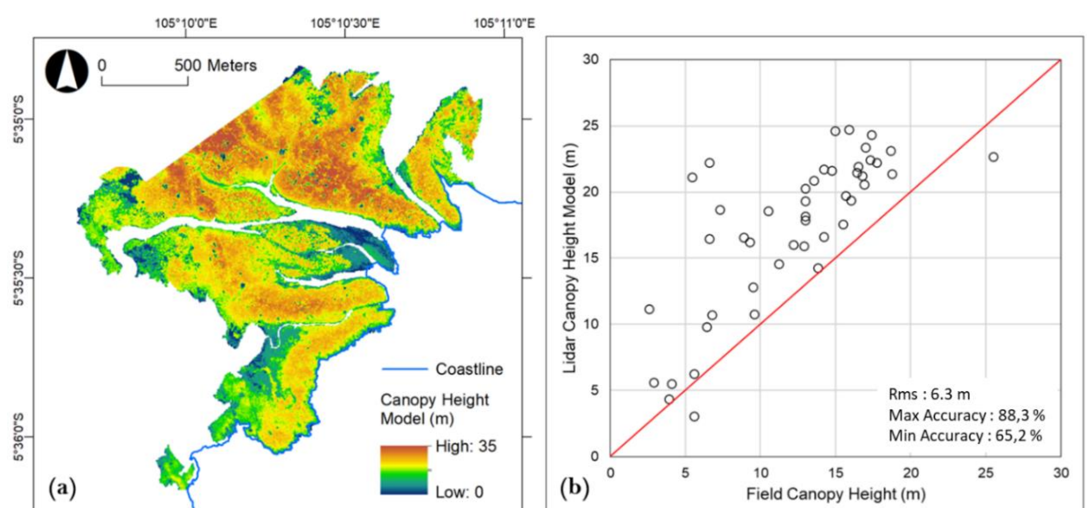
Information Specifications issued by the National Standardization Agency in 2020. Information collection included lifeforms, tree height, and canopy cover percentage to describe field vegetation structure classes. The lifeform was visually observed, canopy closure percentage was measured using hemispherical photography techniques, and tree canopy height was measured using a laser range finder on each tree within the plot. The accuracy of the classification results for vegetation structure is calculated using a error matrix, a technique commonly employed in assessing the outcomes of remote sensing data classification (Congalton, 1991). In addition, the canopy height model and canopy cover percentage were also validated by calculating the root mean square error (RMSE). Both of these data have ratio information, so their accuracy can be estimated by converting the RMSE value to a 95% Confidence Level (95 CL) (Kamal et al., 2021; Wicaksono et al., 2011).

3. Result and Discussion

3.1. *Canopy Height Model Results*

The results of the CHM based on LiDAR data show that the mangroves in Teluk Ratai have a maximum canopy height of 35 meters, which is nearly the height of the tallest mangrove in the world at 39 meters based on a global (Aslan & Aljahdali, 2022). The canopy height model also reveals that the average height of the mangroves in the study area is 18 meters. The high canopy of the mangroves in the study area indicates the potential for high surface carbon stocks, as previous studies have shown a strong correlation between canopy height models and aboveground carbon stocks in mangroves (Aslan & Aljahdali, 2022; Simard et al., 2006). Furthermore, the height of mangrove vegetation in the research area indicates that the mangrove habitat in the Teluk Ratai region has geographical physical conditions that strongly support mangrove growth, especially in terms of salinity levels (Kodikara et al., 2018).

The validation data used in this study consists of 10x10 meter survey plots, which might contain more than one individual tree. The pit-free algorithm used in the CHM tends to overestimate the maximum canopy height of trees compared to the average tree height in the field. The spatial distribution of CHM can be seen in Figure 5a; most of the high mangrove tree are located in the middle of the study site with the maximum tree height of 35 meters. Plot 1:1 in Figure 5b shows that the CHM tends to give estimates that are too high compared to the average tree height in the field. It is because the pit-free algorithm searches for the highest z-value in each grid/pixel of the LiDAR point cloud data (Khosravipour et al., 2014). In addition, field checks indicate that the tallest tree canopy in the survey plot tends to overshadow the canopy of the trees below.



Source: data analysis, 2023

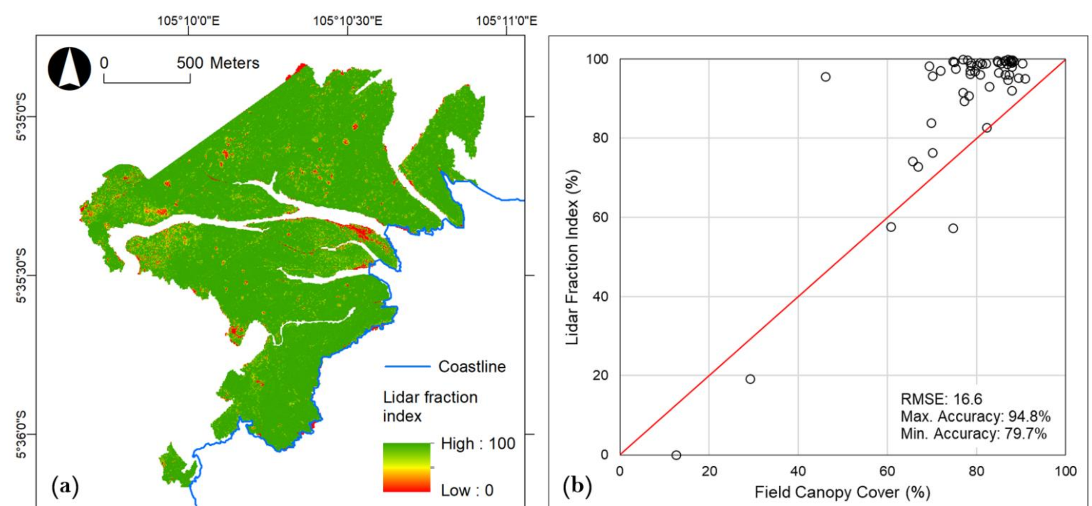
Figure 5. The CHM Results: (a) LiDAR-based CHM, and
(b) 1:1 Plot of CHM Compared to the Maximum Tree Height in the Field.

The performance of the CHM using airborne LiDAR data in this study shows good results. The accuracy test calculations show that the canopy height model has an error of 3.1 meters and an accuracy range of 82.6-88.3% (minimum-maximum accuracy) compared to the maximum height in the field. On the other hand, the performance of the canopy height model will be worse, with an RMSE of 6 meters and an accuracy range of 65.5-88.3% if compared to the average height in the field. The use of a laser range finder instrument in the field is indicated as one of the factors that may have contributed to the less optimal validation test results. The use of a laser range finder instrument has difficulties in targeting the top point of trees due to the dense mangroves. Therefore, it is highly recommended in future research to test the CHM model with Terrestrial LiDAR data to get more representative accuracy results.

3.2. Percent Canopy Cover Estimation

Based on the analysis of LiDAR data, the study area showed a relative percent canopy cover with an average density of 94%. The percentage of canopy cover is considered highly reasonable, as mentioned by Juniansah et al. (2018), who stated that the Teluk Ratai region possesses a complex mangrove vegetation structure. It indicates that the study area is a natural mangrove ecosystem with suitable habitat conditions. The high canopy cover percentage also indicates minimal human activities in the mangrove ecosystem (Kamal, et al., 2016). This result is consistent with findings that high canopy cover levels can indicate a healthy mangrove ecosystem (Nurdiansah & Dharmawan, 2021; Nicolas et al., 2004). However, field checks showed disturbances caused by natural factors such as lightning strikes, resulting in some locations in the study area with open canopy conditions.

Research on LFC models for estimating mangrove canopy cover is still very limited. In terms of performance, the LFC model using airborne LiDAR tends to overestimate canopy cover (Figure 6a). It can be observed in the 1:1 plot presented in Figure 6b, where the point distribution is above the diagonal line. However, the validation test results showed good accuracy, with an RMS error of 16.6% and an accuracy range of 79.6% - 94.8%. Nevertheless, the sample distribution in the validation test was sub-optimal due to the low number of samples at low canopy cover percentages caused by the dominance of dense mangroves in the study area. Future studies may require developing an empirical modeling approach that links LFC values with canopy cover percentage in the field. Therefore, a more comprehensive scientific study is necessary to optimize the canopy cover percentage modeling using LiDAR data for mangrove vegetation.



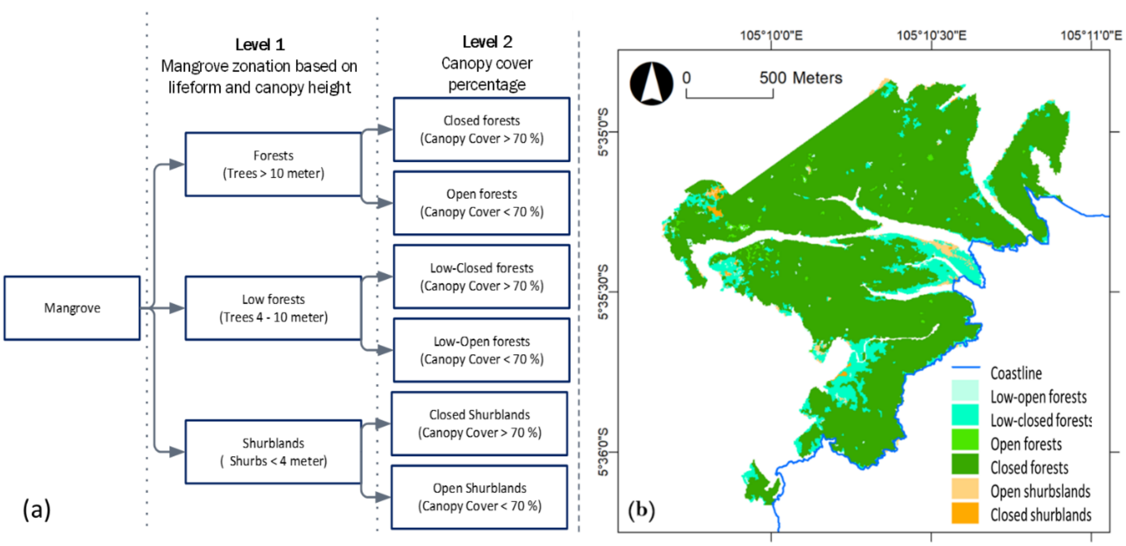
Source: data analysis, 2023

Figure 6. (a) Canopy Cover Percentage Model of LFC, and
(b) 1:1 plot of LFC Model Compared to the Average Canopy Percentage Cover.

3.3. Mangrove Vegetation Structure Classification

A classification system adapted from the scheme developed by Specht (1970, in Saenger, 2002) was used to classify mangrove vegetation structure. It organizes vegetation structure classes based on attributes of lifeform, canopy height, and vegetation cover. Therefore, this study employs a multi-level scheme that divides classes at level 1 based on lifeform zoning patterns and tree height variations into four classes, namely shrublands (<3 m), low forests (3-10 meters), and tall forests (>10 meters). The height class division is based on the fact that mangrove shrub communities have an average height of fewer than 4 meters, while forest classes have an average tree height of more than 4 meters. At second level, mangrove vegetation zoning classes are divided based on the percentage of canopy cover into two classes, closed (>70%) and open (<30%). It is intended to facilitate the understanding and grouping of mangrove vegetation structures (Figure 7a).

Figure 7b shows that open shrublands are usually found in flat estuary mudflats. These open shrublands have low elevation, indicating high soil salinity due to the high intensity of tides. Ahmed et al. (2022) state that high soil salinity is a major factor causing stunted mangrove growth. The closed shrublands class is rarely found in flat estuary mudflats. This class is usually found in the back zone of mangroves with higher elevation and very sheltered from the beach, and it is dominated by the Nypa fruticans species. On the other hand, the closed forests class is an old mangrove community that is characterized by the dominance of Rhizophora apiculata and Sonneratia alba species growing tall in the study area. The closed forests have high surface carbon reserves, indicating that mangroves grow in suitable habitats with minimal human disturbance. However, some open canopy areas can be found within the forest community due to lightning strikes. In addition to the mentioned species, several other species were found in the study area, such as Rhizophora mucronata, Avicennia marina, Acrostichum aureum, Xylocarpus moluccensis, and Xylocarpus granatum (Wijaya et al., 2023).



Source: data analysis, 2023

Figure 7. A multi-level Scheme of Mangrove Vegetation Structure classification.

The accuracy assessment results show that the classification of vegetation structures using airborne LiDAR technology has an overall accuracy of 77%. As shown in Table 2, the lowest producer accuracy is found in the low-closed forests, which is dominated by vegetation lifeforms of shrubs. This is due to the many mangroves with shrub lifeforms that can grow to heights of >4 meters. To avoid this error, other variables may be needed in addition to the canopy height model to separate mangrove vegetation lifeforms. On the other hand, the closed forests class found to be open during fieldwork was due to the distance between the airborne LiDAR acquisition and the field check time, which was separated by almost two years, resulting in changes in the canopy cover conditions in some locations.

Table 2. An Error Matrix of the Mangrove Vegetation Structure Mapping Result

		Low-open Forests	Low-closed Forests	Open Forests	Closed Forests	Open Shrublands	Closed Shrublands	Total	User's Accuracy
CLASSIFICATION	Low-open Forest	1					1	1	50%
	Low-closed Forest		4		2	2	1	4	44%
	Open Forests	1		3				4	75%
	Closed Forests		1	1	36			38	95%
	Open Shrublands	1	1			2	1	6	40%
	Closed Shrublands	1				1	1	8	33%
	Total	4	6	4	38	5	4	61	
	Producer's Accuracy	25%	67%	75%	95%	40%	25%	Overall Accuracy 77 %	

Source: Analysis, 2023

4. Conclusion

Airborne LiDAR data produced an accurate and effective mangrove vegetation structure map. The CHM derived using the pit-free algorithm is able to represent the maximum tree height with an error range of 3.17 meters and an accuracy of 82.3 - 88.6%. The high RMSE is due to the use of a laser range finder for field measurements, which resulted in less accurate measurement results. The use of a laser range finder has limitations in measuring the height of the tallest tree canopy due to the dense mangrove vegetation. The dense mangrove canopy limits the visual observation of the tallest tree point from the laser range finder. Hence, it result in a consistent overestimation of the mangrove canopy height from field observation when being compared to LiDAR data. On the other hand, the canopy percentage model using LFC tends to overestimate with an error range of 16.6% and an accuracy of 79.6 - 94.7%. Developing a more accurate empirical equation to model LFC is strongly recommended for future research. The classification results using vegetation structure data show a total accuracy of 77%. The most significant classification error is due to the inability to distinguish between mangrove shrubs and tree lifeforms based on height. In the study site, there are mangroves with shrub lifeforms with a height of more than 4 meters.

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6. References

Ahmed, S., Sarker, S. K., Friess, D. A., Kamruzzaman, M., Jacobs, M., Islam, M. A., Alam, M. A., Suvo, M. J., Sani, M. N. H., Dey, T., Naabeh, C. S. S., & Pretzsch, H. (2022). Salinity reduces site quality and mangrove forest functions. From monitoring to understanding. *Science of the Total Environment*, *853*, 158662. [Crossref]

Almeida, D. R. ., Stark, S. C., Chazdon, R., Nelson, B. W., Cesar, R. G., Meli, P., Gorgens, E. B., Duarte, M. M., Valbuena, R., Moreno, V. S., Mendes, A. F., Amazonas, N., Gonçalves, N. B., Silva, C. A., Schietti, J., & Brancalion, P. H. S. (2019). The effectiveness of lidar remote sensing for monitoring forest cover attributes and landscape restoration. *Forest Ecology and Management*, *438*, 34–43. [Crossref]

Almeida, P. M. M. de., Madureira Cruz, C. B., Amaral, F. G., Almeida Furtado, L. F., dos Santos Duarte, G., da Silva, G. F., Silva de Barros, R., Pereira Abrantes Marques, J. V. F., Cupertino Bastos, R. M., dos Santos Rosario, E., Santos, V. F., Alves, A., de Oliveira Chaves, F., & Gomes Soares, M. L. (2020). Mangrove Typology: A Proposal for Mapping based on High Spatial Resolution Orbital Remote Sensing. *Journal of Coastal Research*, *95*(SI), 1. [Crossref]

Alongi, D. M. (2009). The Energetics of Mangrove Forests. Dordrecht: Springer.

Arjasakusuma, S., Swahyu Kusuma, S., & Phinn, S. (2020). Evaluating variable selection and machine learning algorithms for estimating forest heights by combining lidar and hyperspectral data. *ISPRS International Journal of Geo-Information*, *9*(9), 507.

Armston, J. D. (2009). Prediction and validation of foliage projective cover from Landsat-5 TM and Landsat-7 ETM+ imagery. *Journal of Applied Remote Sensing*, *3*(1), 033540. [Crossref]

Aslan, A., & Aljahdali, M. O. (2022). Characterizing Global Patterns of Mangrove Canopy Height and Aboveground Biomass Derived from SRTM Data. *Forests*, *13*(10). [Crossref]

Bakx, T. R. M., Koma, Z., Seijmonsbergen, A. C., & Kissling, W. D. (2019). Use and categorization of light detection and ranging vegetation metrics in avian diversity and species distribution research. *Diversity and Distributions*, *25*(7), 1045–1059. [Crossref]

Barenblitt, A., Fatoyinbo, L., Thomas, N., Stovall, A., de Sousa, C., Nwobi, C., & Duncanson, L. (2023). Invasion in the Niger Delta: remote sensing of mangrove conversion to invasive Nypa fruticans from 2015 to 2020. *Remote Sensing in Ecology and Conservation*, *10*(1), 5-23. [Crossref]

Chianucci, F. (2019). An overview of in situ digital canopy photography in forestry. *Canadian Journal of Forest Research*, 227–242. [Crossref]

Congalton, R. G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment*, *37*(1), 35–46. [Crossref]

Coops, N. C., Tompalski, P., Goodbody, T. R. H., Queinnec, M., Luther, J. E., Bolton, D. K., White, J. C., Wulder, M. A., van Lier, O. R., & Hermosilla, T. (2021). Modelling lidar-derived estimates of forest attributes over space and time: A review of approaches and future trends. *Remote Sensing of Environment*, *260*, 112477. [Crossref]

Duke, N. C., Ball, M. C., & Ellison, J. C. (1998). Factors influencing biodiversity and distributional gradients in mangroves. *Global Ecology and Biogeography Letters*, *7*(1), 27–47. [Crossref]

Dwiputra, M. A., & Mustofa, A. (2021). The Comparison of RGB 564 and RGB 573 Band Composite of Landsat 8 for Mangrove Vegetation Distribution Identification on Pahawang Island, Lampung. *IOP Conference Series: Earth and Environmental Science*, *830*(1). [Crossref]

Ehbrecht, M., Seidel, D., Annighöfer, P., Kreft, H., Köhler, M., Zemp, D. C., Puettmann, K., Nilus, R., Babweteera, F., Willim, K., Stiers, M., Soto, D., Boehmer, H. J., Fisichelli, N., Burnett, M., Juday, G., Stephens, S. L., & Ammer, C. (2021). Global patterns and climatic controls of forest structural complexity. *Nature Communications*, *12*(1), 1–12. [Crossref]

Guo, X., Coops, N. C., Tompalski, P., Nielsen, S. E., Bater, C. W., & John Stadt, J. (2017). Regional mapping of vegetation structure for biodiversity monitoring using airborne lidar data. *Ecological Informatics*, *38*, 50–61. [Crossref]

FAO. (2007). The world's mangroves 1980-2005. FAO Forestry Paper, 153, 89.

Frazer, G. W., Canham, C. D., & Lertzman, K. P. (1999). Gap Light Analyzer (GLA), Version 2.0: Imaging software to extract canopy structure and gap light transmission indices from true-colour fisheye photographs, users manual and program documentation. Millbrook, New York: Simon Fraser University, Burnaby, British Columbia, and the Institute of Ecosystem Studies.

Hopkinson, C., & Chasmer, L. (2009). Testing LiDAR models of fractional cover across multiple forest ecozones. *Remote Sensing of Environment*, *113(*1), 275–288. [Crossref]

Jennings, S. B., Brown, N. D., & Sheil, D. (1999). Assessing forest canopies and understorey illumination: Canopy closure, canopy cover and other measures. *Forestry*, *72*(1), 59–73. [Crossref]

Juniansah, A., Tama, G. C., Febriani, K. R., Baharain, M. N., Kanekaputra, T., Wulandari, Y. S., & Kamal, M. (2018). Mangrove Leaf Area Index Estimation Using Sentinel 2A Imagery in Teluk Ratai, Pesawaran Lampung. *IOP Conference Series: Earth and Environmental Science*, *165*(1). [Crossref]

Kamal, M., Hartono, H., Wicaksono, P., Adi, N. S., & Arjasakusuma, S. (2016). Assessment of Mangrove Forest Degradation Through Canopy Fractional Cover in Karimunjawa Island, Central Java, Indonesia. *Geoplanning: Journal of Geomatics and Planning*, *3*(2), 107. [Crossref]

Kamal, M., Phinn, S., & Johansen, K. (2015). Object-based approach for multi-scale mangrove composition mapping using multiresolution image datasets. In *Remote Sensing*, *7*(4). [Crossref]

Kamal, M., Phinn, S., & Johansen, K. (2016). Assessment of multiresolution image data for mangrove leaf area index mapping. *Remote Sensing of Environment*, *176*, 242–254. [Crossref]

Kamal, M., Sidik, F., Prananda, A. R. A., & Mahardhika, S. A. (2021). Mapping Leaf Area Index of restored mangroves using WorldView-2 imagery in Perancak Estuary, Bali, Indonesia. *Remote Sensing Applications: Society and Environment*, *23*, 100567. [Crossref]

Khosravipour, A., Skidmore, A. K., Isenburg, M., Wang, T., & Hussin, Y. A. (2014). Generating pit-free canopy height models from airborne lidar. *Photogrammetric Engineering and Remote Sensing*, *80*(9), 863–872. [Crossref]

Kodikara, K. A. S., Jayatissa, L. P., Huxham, M., Dahdouh-Guebas, F., & Koedam, N. (2018). The effects of salinity on growth and survival of mangrove seedlings changes with age. *Acta Botanica Brasilica*, *32*(1), 37–46. [Crossref]

Korhonen, L., Korhonen, K. T., Rautiainen, M., & Stenberg, P. (2006). Estimation of forest canopy cover: A comparison of field measurement techniques. *Silva Fennica*, *40*(4), 577–588. [Crossref]

Lefsky, M. A., Cohen, W. B., Parker, G. G., & Harding, D. J. (2002). Lidar remote sensing for ecosystem studies. *BioScience*, *52*(1), 19–30. [Crossref]

Li, Q., Wong, F. K. K., & Fung, T. (2019). Classification of mangrove species using combined WordView-3 and LiDAR data in Mai Po Nature Reserve, Hong Kong. *Remote Sensing*, *11*(18), 1–17. [Crossref]

Li, Q., Wong, F. K. K., & Fung, T. (2021). Mapping multi-layered mangroves from multispectral, hyperspectral, and LiDAR data. *Remote Sensing of Environment*, *258*, 112403. [Crossref]

Lucas, R., Lule, A. V., Rodríguez, M. T., Kamal, M., Thomas, N., Asbridge, E., & Kuenzer, C. (2017). Spatial ecology of mangrove forests: A remote sensing perspective. *Mangrove ecosystems: A global biogeographic perspective: Structure, function, and services*, 87-112.

Luther, J. E., Fournier, R. A., van Lier, O. R., & Bujold, M. (2019). Extending ALS-based mapping of forest attributes with medium resolution satellite and environmental data. *Remote Sensing*, *11*(9). [Crossref]

Mahoney, C., Hall, R. J., Hopkinson, C., Filiatrault, M., Beaudoin, A., & Chen, Q. (2018). A forest attribute mapping framework: A pilot study in a Northern boreal forest, Northwest Territories, Canada. *Remote Sensing*, *10*(9). [Crossref]

Ministry of Environment and Forestry. (2021). Peta Mangrove Nasional.

Murray, N. J., Phinn, S. R., DeWitt, M., Ferrari, R., Johnston, R., Lyons, M. B., Clinton, N., Thau, D., & Fuller, R. A. (2019). The global distribution and trajectory of tidal flats. *Nature*, *565*(7738), 222–225. [Crossref]

Nabilah, R., Sitanggang, F. I., & Rahayu, Y. (2021). Mangrove Species Diversity, Stand Structure, and Zonation - A Case Study at Pahawang Kecil Island. *IOP Conference Series: Earth and Environmental Science*, *830*(1). [Crossref]

National Standardization Agency. (2020). SNI 7717:2020 Spesifikasi Informasi Geospasial Mangrove.

Nicolas, J., Schaduw, W., Bachmid, F., Reinhart, G., Lengkong, E. M., Maleke, D. C., Upara, U., Lasut, H. E., Mamesah, J., Azis, A., Tamarol, Y. L., Sulastri, H., Puteri, S. M. A., & Saladi, J. D. (2004). Mangrove Health Index and Carbon Potential of Mangrove Vegetation in Marine Tourism Area of Nusantara Dian Center, Molas Village, Bunaken District, North Sulawesi Province. 201.

Nurdiansah, D., & Dharmawan, I. W. E. (2021). Struktur Dan Kondisi Kesehatan Komunitas Mangrove Di Pulau Middleburg-Miossu, Papua Barat. *Jurnal Ilmu Dan Teknologi Kelautan Tropis*, *13*(1), 81–96. [Crossref]

Pasaribu, R. A., Aditama, F. A., & Setyabudi, P. (2021). Object-based image analysis (OBIA) for mapping mangrove using Unmanned Aerial Vehicle (UAV) on Tidung Kecil Island, Kepulauan Seribu, DKI Jakarta Province. *IOP Conference Series: Earth and Environmental Science*, *944*(1). [Crossref]

Poorazimy, M., Ronoud, G., Yu, X., Luoma, V., Hyyppä, J., Saarinen, N., Kankare, V., & Vastaranta, M. (2022). Feasibility of Bi-Temporal Airborne Laser Scanning Data in Detecting Species-Specific Individual Tree Crown Growth of Boreal Forests. *Remote Sensing*, *14*(19). [Crossref]

Ou, J., Tian, Y., Zhang, Q., Xie, X., Zhang, Y., Tao, J., & Lin, J. (2023). Coupling UAV Hyperspectral and LiDAR Data for Mangrove Classification Using XGBoost in China's Pinglu Canal Estuary. *Forests*, *14*(9). [Crossref]

Saenger, P. (2002). *Mangrove Ecology, Silviculture and Conservation. In Mangrove Ecology, Silviculture and Conservation*. Springer Science & Business Media.[Crossref]

Simard, M., Zhang, K., Rivera-Monroy, V. H., Ross, M. S., Ruiz, P. L., Castañeda-Moya, E., Twilley, R. R., & Rodriguez, E. (2006). Mapping height and biomass of mangrove forests in Everglades National Park with SRTM elevation data. *Photogrammetric Engineering and Remote Sensing*, *72*(3), 299–311. [Crossref]

Spalding, M., Blasco, F., & Field, C. (1997). World Mangrove Atlas. https://archive.org/details/worldmangroveatl97spal

Wang, D., Wan, B., Qiu, P., Su, Y., Guo, Q., & Wu, X. (2018). Artificial mangrove species mapping using Pléiades-1: An evaluation of pixel-based and object-based classifications with selected machine learning algorithms. *Remote Sensing*, *10*(2). [Crossref]

Wang, D., Wan, B., Qiu, P., Tan, X., & Zhang, Q. (2022). Mapping mangrove species using combined UAV-LiDAR and Sentinel-2 data: Feature selection and point density effects. *Advances in Space Research*, *69*(3), 1494–1512. [Crossref]

Wicaksono, P., Danoedoro, P., Hartono, H., Nehren, U., & Ribbe, L. (2011). Preliminary work of mangrove ecosystem carbon stock mapping in small island using remote sensing: above and below ground carbon stock mapping on medium resolution satellite image. *Remote Sensing for Agriculture, Ecosystems, and Hydrology XIII*, *8174*, 408-417. SPIE. [Crossref]

Wijaya, M. S., Kamal, M., & Widayani, P. (2023). Mapping of Mangrove Composition in Ratai Bay , Lampung Province Using Pleiades-1 Satellite Imagery. *God of Earth*, *23*(2), 107–122. [Crossref]

Xie, Y., Sha, Z., & Yu, M. (2008). Remote sensing imagery in vegetation mapping: a review. *Journal of Plant Ecology*, *1*(1), 9–23. [Crossref]

Yin, D., & Wang, L. (2019). Individual mangrove tree measurement using UAV-based LiDAR data: Possibilities and challenges. *Remote Sensing of Environment*, *223*, 34–49. [Crossref]

Zhang, K., Houle, P. A., Ross, M. S., Ruiz, P. L., & Simard, M. (2006). Airborne laser mapping of mangroves on the biscayne bay coast, Miami, Florida. *International Geoscience and Remote Sensing Symposium (IGARSS)*, 3733–3737. [Crossref]