Predictive Modelling of Mangrove Above Ground Biomass through the Integration of Spectral Indices and Field-Based Allometric Data

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Abstract *This study aims to develop a predictive model for estimating Above Ground Biomass (AGB) of mangroves by integrating various vegetation spectral indices. The research addresses the challenge of accurately estimating AGB by combining high resolution satellite imagery with field-based allometric data obtained through non-destructive surveys in the mangrove area of East Surabaya Coast. Allometric data sampling was conducted using purposive random sampling with dominantly 30 x 30 meters plot area according to SNI 7724:2019. The data retrieved was circumference or Girth Breast Height (GBH) with standard at 1.3 meters from the ground surface, measurement was conducted for all sapling, poles, and stands of mangrove trees in each plot. The data acquired also height, soil moisture, salinity, and pH level of the plot area The methodology involves spectral indices calculation such as the Normalized Difference Vegetation Index (NDVI), Normalized Difference Moisture Index (NDMI), and Combined Mangrove Recognition Index (CMRI) derived from Worldview-2 Satellite Imagery. These spectral indices are integrated with field derived biomass values to develop multiple predictive models. Allometric equation that incorporate DBH and Height displayed better relation value between Aboveground Biomass with its parameter compared to Aboveground Biomass that only incorporate DBH. The AGB model with a DBH^2H parameter has higher R square value at 0.61 compared to the AGB model with a DBH parameter of 0.39. Stock carbon modeling developed using vegetation indices showed the relationship between field carbon stock data and pixel values in the vegetation index transformation. The results of the correlation test on NDVI and CMRI were positive, meanwhile NDWI showed negative correlation. According to R^2 value, NDWI displayed best relation value compared to NDVI and CMRI, even thought the relation were negative with 0.543. The resulting best – fit model is expected to serve as a reference for future AGB estimation and contribute to the development of technical standards for carbon stock assessment in coastal mangrove ecosystem.*

Keywords: *Above Ground Biomass, Allometric, Mangrove, Spectral Indices, Predictive Model*

Introduction

Mangrove ecosystem has potential ability to store carbon dioxide better than other forest ecosystem (Alongi, 2012) Some of the reasons why mangroves are considered superior biomass stores compared to terrestrial trees include their large, complex taproots and respiratory roots. This root system stores a significant amount of belowground biomass (root biomass), often exceeding that of terrestrial forest trees (Arnaud et al., 2023). Furthermore, much of the mangrove carbon reserves are stored in the very deep and stable soil (soil carbon). This allows mangroves to act as a long-term carbon sink (Adame et al., 2024).

The calculation of mangrove carbon stocks is of critical importance in the present era, serving multiple functions that include climate change mitigation, the formulation of mangrove-related policy and management strategies, and the economic valuation of mangroves within the broader context of coastal blue carbon.

From a climate change mitigation perspective, carbon stock assessments provide an essential basis for estimating potential carbon emissions that could result from mangrove deforestation or degradation, thereby informing emissions reduction strategies. As a foundation for policy and management, carbon stock data enables governments and environmental managers to design evidence-based conservation, restoration, and zoning policies for mangrove ecosystems. In terms of economic assessment, carbon stock information can be applied to quantify the value of ecological services associated with mangroves, such as carbon trading schemes or payments for environmental services, both of which can generate financial incentives to ensure the preservation and rehabilitation of mangrove habitats.

The measurement of carbon stocks, particularly for the aboveground biomass (AGB) of mangroves, using the allometric method has become a standardized approach to support climate research, conservation initiatives, and carbon trading schemes (Ávila-Acosta et al., 2024). The allometric approach enables the estimation of biomass through the measurement of simple tree parameters—such as stem diameter, tree height, and wood density—thereby providing a non-destructive alternative to traditional methods involving tree felling and oven-drying. Moreover, this method can be efficiently applied to a large number of trees within a plot in a relatively short period of time.

The development of allometric equations for mangroves, as established by Komiyama et al., (2005) has provided models that yield biomass estimation from Diameter Breast Height (DBH) with high accuracy compared to destructive methods, with reported correlation values of approximately 0.979 for AGB. These equations are considered representative across different mangrove species, as they incorporate wood density to account for the unique structural characteristics of mangrove trees.

Height of mangrove considered an important parameter to estimate mangrove biomass and could be a vital addition in tandem with DBH. The best model that accommodates DBH and height has a higher fit and precision compared to the model that only uses DBH (Santos et al., 2017). This statement also supported Nilmini Wijeyaratne & Liyanage, (2020) that models using only DBH have a lower R^2 than models that also include height and other structural variables.

A spectral index is a combination of reflectance values from various wavelength bands (usually from multispectral or hyperspectral sensors). This index utilizes the interaction of vegetation with light, particularly in the visible (VIS), red-edge, and near-infrared (NIR) regions (Xue & Su, 2017).

Spectral indices and biomass are closely related because vegetation spectral indices are designed to capture information about plant health, canopy structure, and chlorophyll content, all of which are related to aboveground biomass (AGB). This statement was supported by Li et al., (2021) that red-edge spectral bands & near-infrared ones had stronger correlation with AGB than visible and SWIR bands, in many cases. Rapiya et al., (2023) also highlights that the red edge indices and traditional vegetation indices using red & NIR bands perform well in estimating AGB, especially at the vegetative/flowering stage when chlorophyll content & canopy structure are clearly visible.

This study used allometric equation to calculate AGB proposed by Thant et al., (2012) using a combination of $DBH^2 \times H$ (including height), to accommodate variations of height in tree structure. This equation is expected to be more accurate in predicting biomass compared to common allometric equation from Komiyama et al., (2005). Field measurements and vegetation indices each have inherent limitations. While field measurements provide high accuracy, they are labor-intensive and time-consuming. In contrast, vegetation indices allow rapid assessments over a wide spatial range but require validation from field-derived biomass data. Therefore, examining the correlation between these two approaches is crucial for developing more reliable and accurate biomass estimation models.

Literature Review

a. Aboveground Biomass (AGB) Parameters

Aboveground Biomass (AGB) refers to the total dry mass of all plant components aboveground, including stems, branches, twigs, leaves, and reproductive parts (Appendix 2 Possible Approach for Estimating CO_2 Emissions from Lands Converted to Permanently Flooded Land: Basis for Future Methodological Development), AGB is often expressed in tons per hectare (ton/ha) or megagrams per hectare (Mg/ha). AGB plays a crucial role in ecological, forestry, and climate change studies because it serves as an indicator of ecosystem productivity and carbon stocks (Brown, 1997 ; Chave et al., 2005).

One method used to measure AGB is the allometric approach, which estimates biomass based on the mathematical relationship between tree morphological variables. Generally, the variables used in allometric equations include Stem diameter at breast height (DBH, 1.3 m above the ground), Tree height (H) and Wood density (ρ).

b. Aboveground Biomass (AGB) Calculation using Allometric Calculation

The field data used in the AGB allometric equation consists of diameter at breast height (DBH), which is the stem diameter measured at breast height, following the model developed by Thant et al in equation 1. In addition to DBH, this equation also includes species-specific wood density values, making it important to identify the mangrove species whose diameters were measured in the field. Afterwards, the amount of carbon stock is calculated from Forest Stand Total Biomass (kg/m^2) using a conversion factor (CF) of 0.47 (Poudel et al., 2023). The allometric equation and the wood density values used in area study are presented below, first equation were developed by Thant et al., 2012 which included DBH and Height, meanwhile equation 2 was developed by Komiyama et al., (2005) which only incorporated DBH in the calculation:

$$WTop=0.22\rho(DBH^2\cdot H)^{0.82} \quad (1)$$

$$WTop=0.251\rho(DBH)^{2.46} \quad (2)$$

WTop = aboveground biomass (kg)

ρ = wood density (g/cm^3)

DBH = diameter at breast height (cm)

H = tree height (m)

Table 1: Mangrove wood density values

Species	Wood density (g/cm^3)	Source
Avicennia alba	0.506	(Komiyama et al., 2005)
Avicennia marina	0.650	(Zanne et al., 2009)
Avicennia officinalis	0.670	(Kauffman & Donato, 2012)
Bruguiera cylindrica	0.720	(Zanne et al., 2009)
Bruguiera gymnorhiza	0.741	(Kauffman & Donato, 2012)
Exoecaria agallocha	0.480	(Zanne et al., 2009)
Rhizophora apiculata	1.050	(Kauffman & Donato, 2012)
Rhizophora mucronata	0.820	(Zanne et al., 2009)
Rhizophora stylosa	0.840	(Zanne et al., 2009)
Sonneratia alba	0.475	(Komiyama et al., 2005)
Sonneratia caseolaris	0.340	(Komiyama et al., 2005)
Xylocarpus moluccensis	0.531	(Komiyama et al., 2005)
Xylocarpus granatum	0.528	(Komiyama et al., 2005)
Xylocarpus moluccensis	0.531	(Komiyama et al., 2005)

c. Vegetation Spectral Indices

Higher Vegetation Indices values indicate denser vegetation with a higher leaf area index. Correlating Vegetation Indices values with observed vegetation density in the field produces a spatially explicit biomass map consistent with the spatial resolution of the image (Howard, 2014).

Some examples of common machine learning applications for vegetation indices are the Normalized Difference Vegetation Index (NDVI) and the Combined Mangrove Recognition Index (CMRI).

Table 2: Vegetation Indices

Spectral Indices	Formula	Source
NDVI (Normalized Different Vegetation Index)	(ρNIR-ρRed)/(ρNIR+ρRed) NIR = Near Infrared Red = Red band	(Rouse et al., 1974)
NDWI (Normalized Difference Water Index)	(ρGreen-ρNIR)/ (ρGreen +ρNIR) NIR = Near Infrared Green = Green band	(Gao, 1996)
CMRI (Combined Mangrove Recognition Index)	NDVI - NDWI	(Gupta et al., 2018)

d. Statistical Analysis

The statistical tests conducted for this study were correlation and regression. The correlation test was conducted to determine the relationship between carbon stock parameters and then compare the resulting coefficient of determination (R^2) values. Correlation was also carried out to compare the correlation level of vegetation spectral indices. Meanwhile, regression analysis was conducted to determine the mathematical values of the independent and dependent variables.

$$R^2=1-\sum(yi-\hat{Y})^2/\sum(yi-\acute{y})^2 \qquad (3)$$

yi = Actual value or true value on the i-th data point

ý = Model predicted value on the i-th data point

Ŷ = Average actual y value

Table 3: Coefficient Determination Interpretation

Coefficient of Determination (R^2) Values	Category/Interpretation
0.01 – 0.29	Weak
0.3 – 0.49	Moderate
0.5 – 1	Strong

Source: (Cohen, 2013)

Methodology

a. Study Area

This study was conducted in the Mangrove Conservation Area on the East Coast of Surabaya, as previously carried out by Alina et al., (2024). The research site is located between 112°47'50" and 112°51'5" east longitude and 7°14'31" and 7°20'57" south latitude, covering an area of 28.73 km². The area of interest (AOI) for this research is illustrated in Figure 1.

Figure 1: Area of Interest

b. Data

This study uses high-resolution satellite imagery from WorldView-2, acquired on February 22, 2024, with a cloud cover of 0.001. WorldView-2 was equipped with several multispectral bands namely blue, green, red, and near-infrared, coastal blue, yellow, red edge, and near-infrared 2. Worldview – 2 satellite imagery utilized in this study were shown in Figure 2.

Table 4: Worldview – 2 Band Parameter

Band	Wavelength	Spatial Resolution on Nadir
Panchromatic (Pan)	450 – 800 nm	0.46 m GSD or (0.52 m on 20° nadir)
Blue Coastal	400 – 450nm	1.8 m GSD or (2.4 m on 20° nadir)
Blue	450 – 510 nm	
Green	510 – 580 nm	
Yellow	585 – 625 nm	
Red	630 – 690 nm	

Band	Wavelength	Spatial Resolution on Nadir
Red-Edge	705 – 745 nm	
NIR 1	770 – 895 nm	
NIR 2	860 – 1040 nm	

Sources : https://earth.esa.int/eogateway/missions/worldview-2

Figure 2: Worldview-2 satellite image of study area

c. Workflow

Figure 3 displayed the workflow conducted for this study. Pre-processing of Worldview 2 Satellite Imagery were mosaic and atmospheric correction as previously conducted in Alina et al., (2024). Allometric calculation was carried out using Equation 1 with wood density according to sources in Table 1. Afterwards NDVI, NDWI, and CMRI raster calculation was conducted according to sources in Table 2.

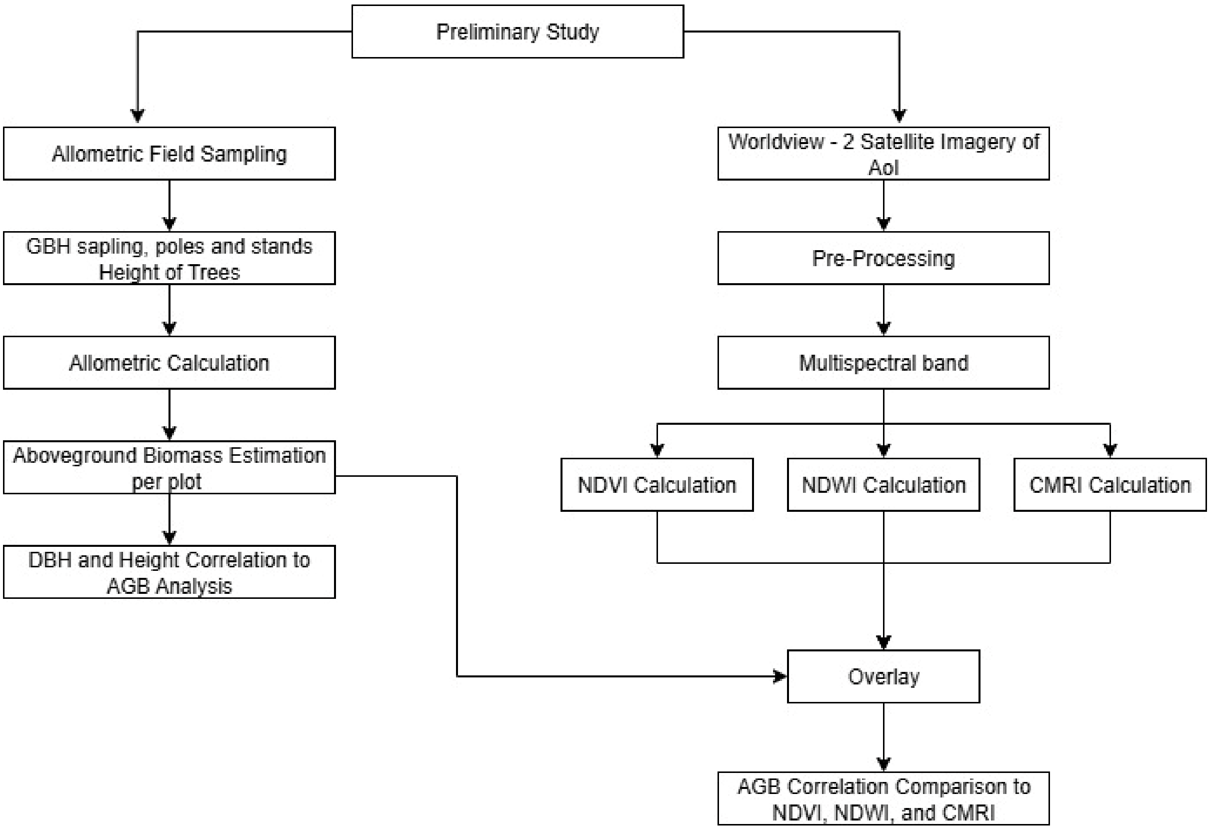


Figure 3: Research Workflow

d. Field Data Retrieval / Allometric Measurement

Field data retrieval was carried out on August 20, 2025 until September 4, 2025. The data retrieved was circumference or Girth Breast Height (GBH) with standard at 1.3 meters from the ground surface (measured from the base of the tree on the upper side if on a slope). Measurement was conducted for all sapling (GBH 2-10 cm), poles (GBH 10-20 cm), and stands (GBH ≥20 cm) of mangrove trees in each plot. Height of the mangrove's tree acquired using rangefinder equipment. Soil moisture, Salinity, and pH level of the plot area also retrieved to complete information regarding the biochemical condition of mangroves.

Sampling was conducted for 40 plot area as shown in Figure 5 using purposive random sampling to cover all East Coast Surabaya region which distributed in Bulak Sub-District, Mulyorejo Sub-District, Sukolilo Sub-District, Rungkut Sub-District and Gunung Anyar Sub-district. Plot sampling area were dominantly 30 x 30 meters, unless there were geographical obstacles in the area, for instance river or deep muddy swamps. Allometric measurement was conducted based on Indonesian National Standard (SNI) 7724:2019

Carbon Stock Measurement and Calculation – Field Measurement for Land-Based Carbon Stock Estimation (Land-Based Carbon Accounting) from Badan Standarisasi Nasional, (2019).

GBH for each sampling, poles and stands then converted to Diameter Breast Height (DBH) by dividing GBH with 3.14. This DBH and Height then used in allometric equation per species, then summed in total to generate carbon stock per plot.

Figure 4: Field Allometric Measurement

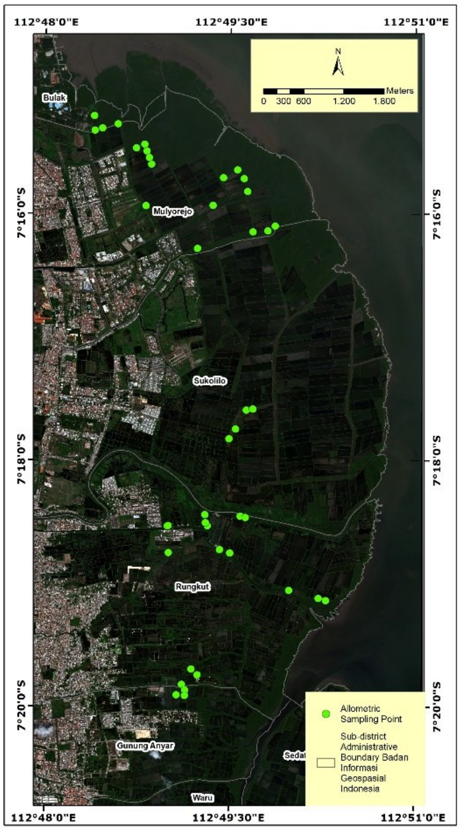


Figure 5: Allometric Sampling Distribution

Results and Discussion

a. Number of Species Derived from Allometric Measurement

According to field allometric measurement that has been conducted, total of mangrove species tree retrieved were shown in Figure 6. Total mangrove trees that has been measured were 4958, with Avicennia marina became the most dominant species with 2590 measured, followed by Bruguiera gymnorhiza with 630 measured and Exoecaria agallocha with 505 measured. The least species found during allometric measurement were Sonneratia alba with only 3 trees found and measured.

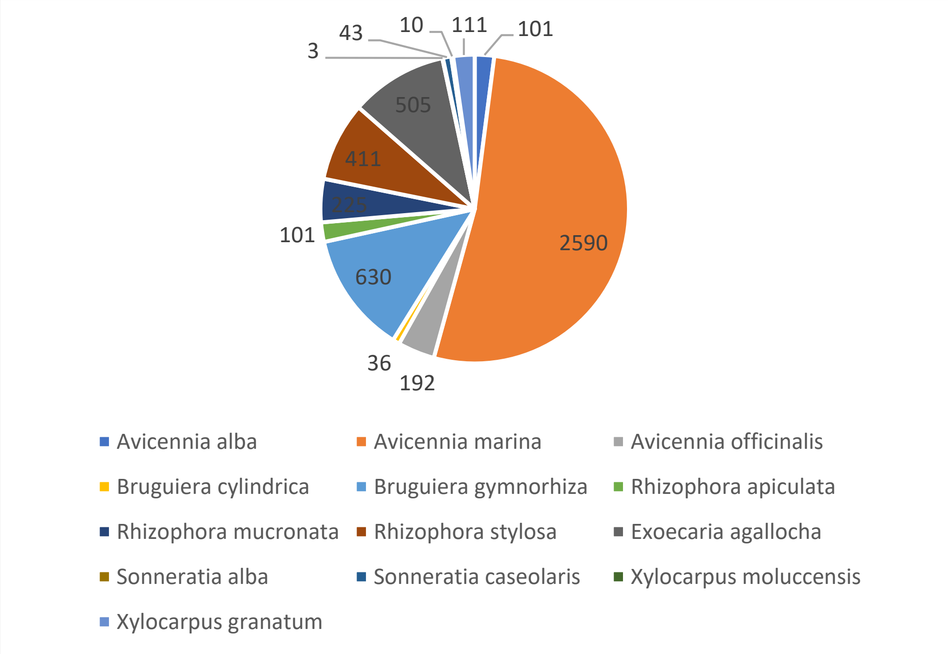


Figure 6: Total of Mangrove Trees Measured per Species

b. Above Ground Biomass Calculation using Allometric Equation

Aboveground Biomass were calculated for each plot using allometric equation number 1 and 2. Each of saplings, poles, and stands were calculated individually then summed for each plot. Biomass generated from Komiyama et al., (2005). Equation relatively resulted in higher biomass calculation compared to biomass value acquired from Thant et al., (2012).

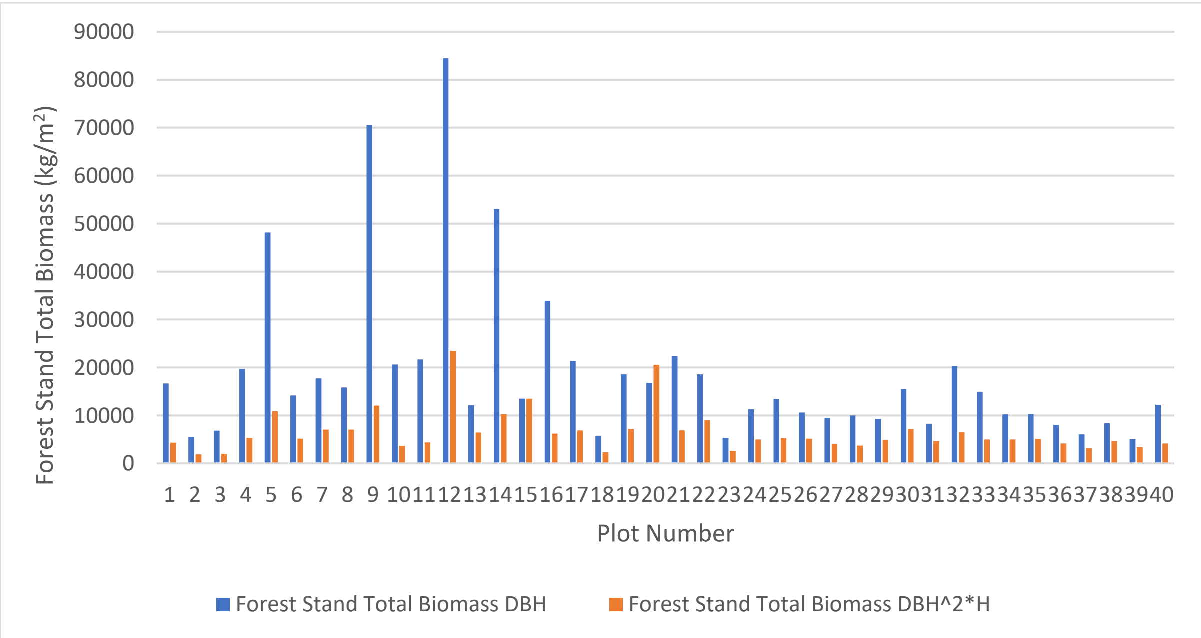


Figure 7: Total Forest Stand Biomass Measured per Plot

c. Comparison of AGB Modelling using DBH and DBH2xHeight Parameter

Different allometric equations were utilized to estimate AGB and the result were displayed in table 5. Table 5 showed respective allometric model used as well as the correlation coefficient value or R^2 of each model after correlation test was conducted to equation which incorporates DBH and equation which incorporates both DBH and height. This comparison showed the relationship level between independent variable DBH and DBH^2 x Height parameter to AGB generated from the equation.

Table 5 : AGB Model Relationship Summary

Regression Statistics	DBH	DBH^2xHeight
Multiple R	0.624	0.78
R Square	0.39	0.61
Adjusted R Square	0.37	0.59
Standard Error	13528.63	2836.25
ANOVA signification value	0.000017	0.00000002
Observations	40	40

Both models have an R Square value above 0.29, however, the AGB model with DBH and height has an R-square value that is almost twice as high. The AGB model with a DBH^2H parameter has higher R square value at 0.61 compared to the AGB model with a DBH parameter of 0.39. The ANOVA results for both models have a Significance $F < 0.05$ (much smaller than 0.01), this indicates that the independent variables (factors) really have a significant effect on the dependent variable. According to Cohen (2013), both DBH only model and DBH and height model, have a moderate and strong correlation respectively.

Table 6 : AGB Model Estimation to DBH

Regression Value to DBH	Coefficients	Standard Error	Relative Standard Error
Intercept	12549.412890	2473.686000	-0.197116
DBH	3.276660	0.665642	0.203146

Table 7 : AGB Model Estimation to DBH^{2}xHeight

Regression Value to DBH ^2 xH	**Coefficients**	**Standard Error**	**Relative Standard Error**
Intercept	2557.832708	795.298500	-0.310927
DBH	0.807400	0.143900	0.178237
HT	3.444900	0.9435900	0.273906

For first model, DBH has relative standard error 0.203146 to AGB Model Estimation, this value derived from Standard Error / |Coefficients| (absolute value of coefficient). It means that DBH in estimation model has about 20% uncertainty relative to its size under 25% than the coefficient itself, thus making the value acceptable.

For second model, DBH has relative standard error 0.178237 to AGB Model Estimation, this value also derived from Standard Error / |Coefficients|. It means that DBH in estimation model has about 17% uncertainty relative to its size. Meanwhile for Height, relative standard error generated was 0.273906, meaning that Height has about 27% uncertainty. The value is slightly over 25% of the coefficient. This is value is not very precise but still acceptable.

d. Calculation of Vegetation Indices NDVI, NDWI and CMRI

NDVI, NDWI, and CMRI were calculated using equation from table 2 using bottom or atmospherically corrected and pre-processed Worldview – 2 Satellite Imagery. The value of spectral indices from each vegetation indices was shown in table 8 below:

Table 8 : Value of Vegetation Indices

Vegetation Indices	**Min Value**	**Max Value**	**Range Value**
NDVI	-0.997802	0.933422	-1 to 1
NDWI	-0.798571	0.998197	-1 to 1
CMRI	-1.996	1.72864	-2 to 2

The calculation of NDVI, NDWI, and CMRI were correct since the value of minimum and maximum value were lies between range value of each spectral indices.

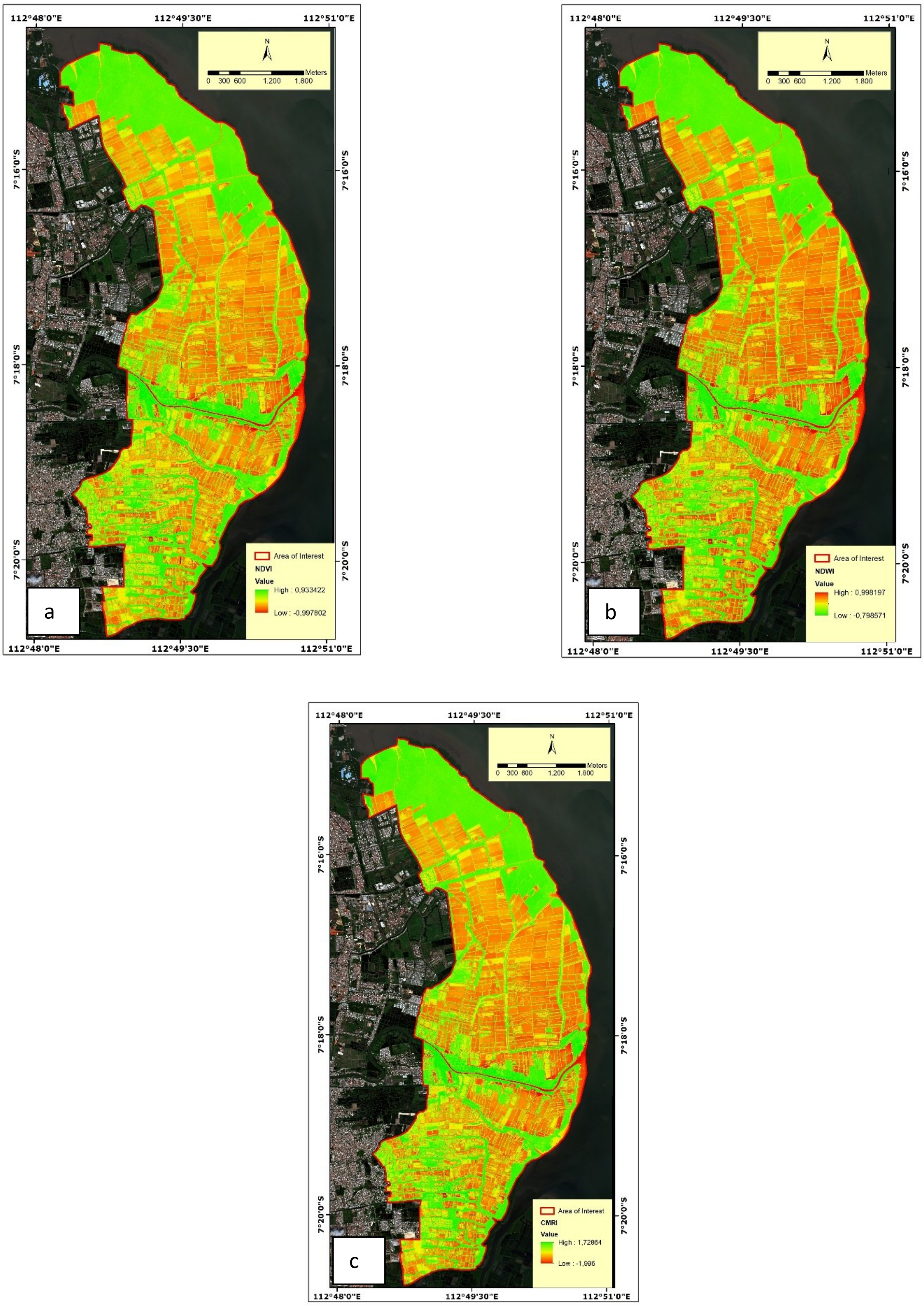
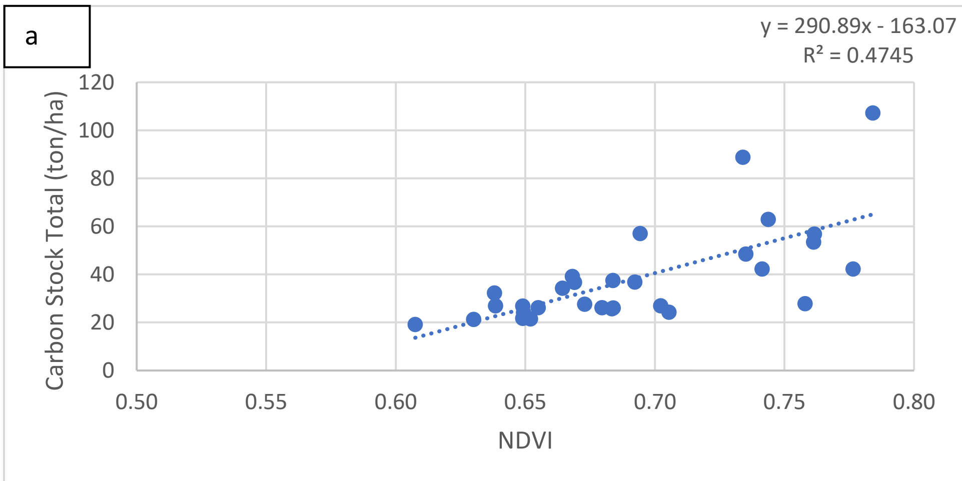
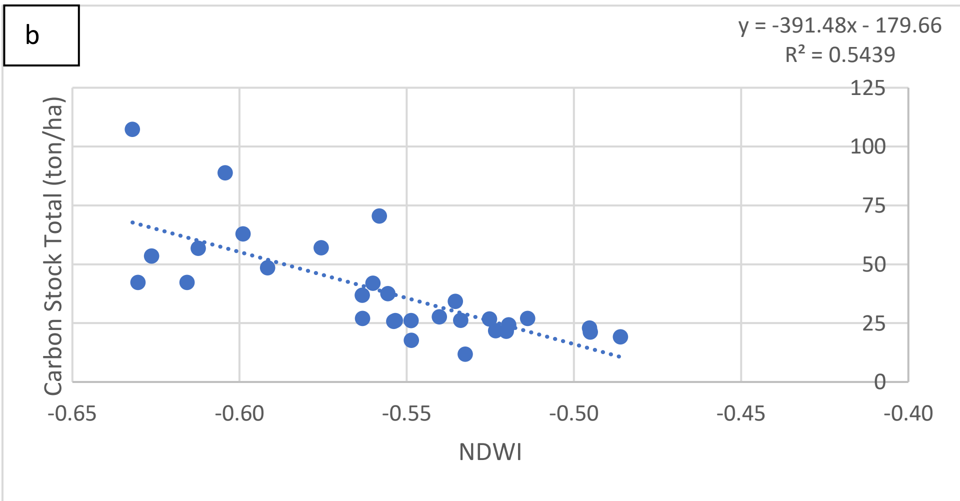


Figure 8: Result of Vegetation Indices (a) NDVI (b) NDWI (c) CMRI

e. Calculation of Correlation Between Vegetation Indices (NDVI, NDWI and CMRI) and Carbon Stock (ton/ha)

As previously stated, the amount of carbon stock is calculated from Forest Stand Total Biomass (kg/m^2). Firstly, forest stand total biomass were converted to ton/ha unit, then thus value was converted to Carbon Stock (ton/ha) using a conversion factor (CF) of 0.47. These Carbon Stock value was correlated to NDVI, NDWI, and CMRI to generate R^2 value. From 40 sample plot area, 30 area were selected as input value to build correlation model.





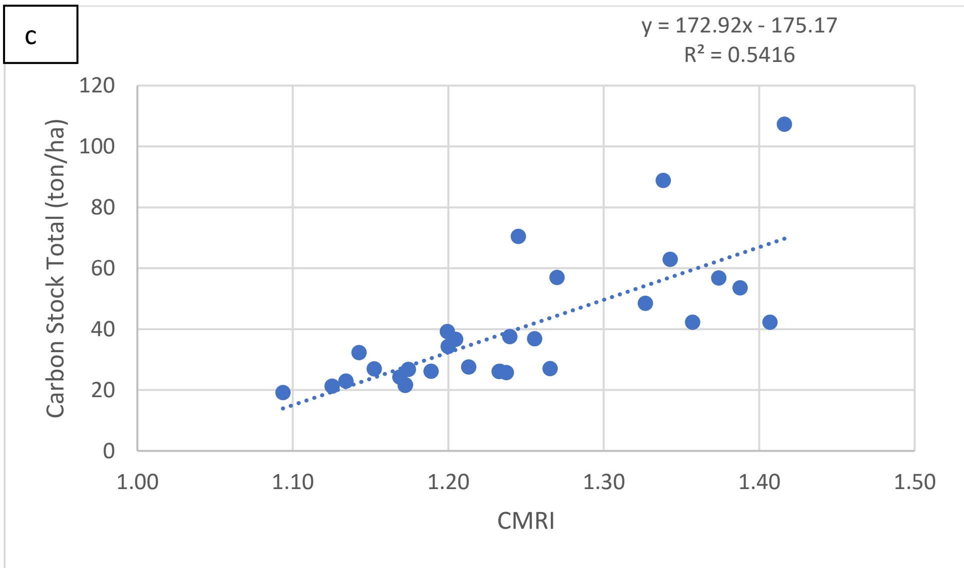


Figure 9: Result of Correlation Between Vegetation Indices and Biomass (a) NDVI (b) NDWI (c) CMRI

Stock carbon modeling developed using vegetation indices showed the relationship between field carbon stock data and pixel values in the vegetation index transformation. The results of the correlation test on NDVI and CMRI were positive, meanwhile NDWI showed negative correlation. The Normalized Difference Vegetation Index (NDVI) transformation has a correlation with a value of 0.475. This relationship was categorized as moderate correlation level. The correlation between the carbon stocks and Normalized Difference Water Index (NDWI) showed correlation with value of 0.543, and this was categorized as strong relation level even though the relation was shown to be negative. Lastly, the Combined Mangrove Recognition Index displayed a correlation with a value of 0.5416, slightly less than NDWI, this value also classified as strong correlation with positive relation. According to this result, NDWI showed greatest value compared to NDVI and CMRI, even though the relation were negative.

Conclusion and Recommendation

According to this study, allometric equation that incorporate DBH and Height displayed better relation value between Aboveground Biomass with its parameter compared to Aboveground Biomass that only incorporate DBH. The AGB model with a DBH^2H parameter has higher R square value at 0.61 compared to the AGB model with a DBH parameter of 0.39. Stock carbon modeling developed using vegetation indices showed the relationship between field carbon stock data and pixel values in the vegetation index transformation. The results of the correlation test on NDVI and CMRI were positive, meanwhile NDWI showed negative correlation. According to R^2 value, NDWI displayed best relation value compared to NDVI and CMRI, even though the relation were negative with 0.543. This finding support prior findings from Kang et al., (2023) that NDWI could be utilized as significant predictors for mapping carbon stocks of wetland species and showing that together with other vegetation indices NDWI helps improve the accuracy of carbon modeling in wetland ecosystems.

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