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Research Article

Utilization of Sentinel-2 Imagery in Mapping the Distribution and Estimation of Mangroves' Carbon Stocks in Bengkulu City

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ABSTRACT

The mangroves' aboveground biomass significantly contributes to the global carbon cycle or economic and ecological values. This makes knowledge about the spatial extent of the mangroves indispensable for policymakers. The sequence of mangroves' condition range also requires remote sensing data to update the geographical information and synthesize carbon stock in Bengkulu. Therefore, this study aims to create a spatial distrribution of mangroves and evaluate their carbon stock in Bengkulu City using Sentinel-2 imagery. The semi-empirical method uses Sentinel-2 imagery through NDVI to appraise and picture the mangroves' aboveground carbon stock. An allometric equation was used to compute the mangroves' aboveground carbon stock from field measurements. Non-linear regression was used to establish a connection between the NDVI calculated from the Sentinel-2 imagery and the mangroves' aboveground biomass measured in the field, which was subsequently used for aboveground carbon estimation. The results showed that mangroves mapping could derive overall accuracy of 89.09%, where the high-density class existed in 135.12 Ha of total area. It was also discovered that Sentinel-2 imagery could estimate mangroves carbon stock up to 61%. The carbon stock estimation based on the imagery has a value of 16.3992 – 115.134 t C/ha, while that of field survey data ranges from 19.69 to 326.06 t C/ha. These results showed that Sentinel-2B spectral data is functional and has a good chance of being able to predict carbon stock.

Keywords : Carbon; mangroves; NDVI; remote sensing; sentinel-2B

1. Introduction

The ecosystem services provided by mangroves are wide-spreading, therefore, their valuable existence is undeniable, particularly for carbon sequestration (Jones et al., 2020; Kusumaningtyas et al., 2022), climate change mitigation (Jennerjahn, 2021; Sjögersten et al., 2021), coastal protection (Karimi et al., 2022), and many socio-economic benefits from ecological function (Trialfhianty et al., 2022). As the particular tropical and sub-tropical vegetation, mangroves inhabit almost all of Indonesia's coastline. This makes it one of the most considerable potential for carbon sequestration by approximately 23% of global mangroves (Suyadi, 2020). The Blue Carbon potential of mangroves is based on the sequestration rate, which is four times more than rainforests (Nyanga, 2020). This indicates the powerhouses' capacity of mangroves to sequester substantial amounts of carbon accounted for the sediment belowground and aboveground biomass. Meanwhile, the mangroves' aboveground biomass is well related to its important function in the context of the global carbon cycle or economic and ecological values. This makes information related to the spatial extent of the mangroves area indispensable (Baloloy et al., 2018).

Recent technological advances have improved both the accuracy and the extent of remote sensing for mapping as well as increased the ability to estimate biomass to calculate mangroves' carbon stock (Bindu et al., 2020; Galidaki et al., 2017). Over decades, a widely-used approach, namely the remote sensing technique allows the monitoring of the extent and changes in mangroves areas (Rudiastuti et al., 2018). Previous investigations have shown that mangroves forests frequently grow in hard-to-access areas. This led to an increase in the importance of remote sensing data exploration to study mangroves.

As a coastal city, Bengkulu has an area of mangroves that spatially spread along the north-south coastline. According to the interpretation result using remote sensing imagery (Anggraini, 2014), mangroves deforestation, degradation, and area conversion due to domestic needs have reduced about 65% of the mangroves area in nature tourism park (TWA) Pantai Panjang and Baai Island, Bengkulu, within 13 years (2000 – 2013). There is an abundance of coastal tourism potencies in Bengkulu City, however research on the supportive aspects of developing mangroves ecotourism is limited. This is because the ecotourism concept concentrates on ecology conservation, economic benefits, and society concerning a spatial approach to achieve a sustainable coastal management strategy (Rudiastuti et al., 2018). Therefore, the spatial aspects related to mangroves have become essential information for stakeholders such as Balai Konservasi Sumber Daya Alam Bengkulu and decision-makers in the city concerning sustainable coastal use.

The spatial information of existing mangroves also shows the importance of optimizing the mangroves conservation and ecotourism in Baai Island since 2017 (Yunita & Edwar, 2019), as well as TWA in Bengkulu. The sequence of mangroves conditions urges the use of remote sensing data to update geospatial information and synthesize their carbon stock. However, the spatially based research on mangroves in the Bengkulu City is still limited (Anggraini, 2014; Senoaji & Hidayat, 2017; Silitonga et al., 2018; Srifitriani et al., 2020). This is because there are no scientific records on mangroves area mapping and carbon stock estimation using 10-meter remote sensing data on Bengkulu Coast. The investigations related to mangroves carbon stock estimation involved various vegetation indexes, where the most prevalent is Normalized Different Vegetation Index (NDVI). The density of plant is a proxy for biomass, which can be measured by the vegetation index (Anand et al., 2020; Perry et al., 2022; Pham et al., 2020; Sharma et al., 2020; Thuy et al., 2020), ARVI and EVI (Siddiq et al., 2020), DVI (Purnamasari et al., 2021). Therefore, this study aims to determine the use of Sentinel-2 imagery in mapping mangroves' spatial distribution and estimating their carbon stock in Bengkulu City.

2. Methods

This research calculated the carbon stock at several field sample locations and determined a link between the Aboveground Biomass (AGB) at field sample points and the NDVI. The combination between field data collection and remote sensing data analysis was also carried out. This involves four main steps, namely (i) image processing, (ii) vegetation index transformation, (iii) ground-truthing and field data collection, and (iv) carbon stock calculations.

2.1 Study Area

Mangroves at Bengkulu City served as the location from September 15-22, 2021 (Figure 1). The six sites were selected to provide a geographically diverse representation of the mangroves ecosystem in the city, which extended to the riverbanks from the estuary. These sites included Pantai Panjang and Baai Nature Park Island, conservation and non-conservation areas. Since the national government recognized both Pantai Panjang and Baai Island as nature parks, they attracted the most visitors and became well-known stations.

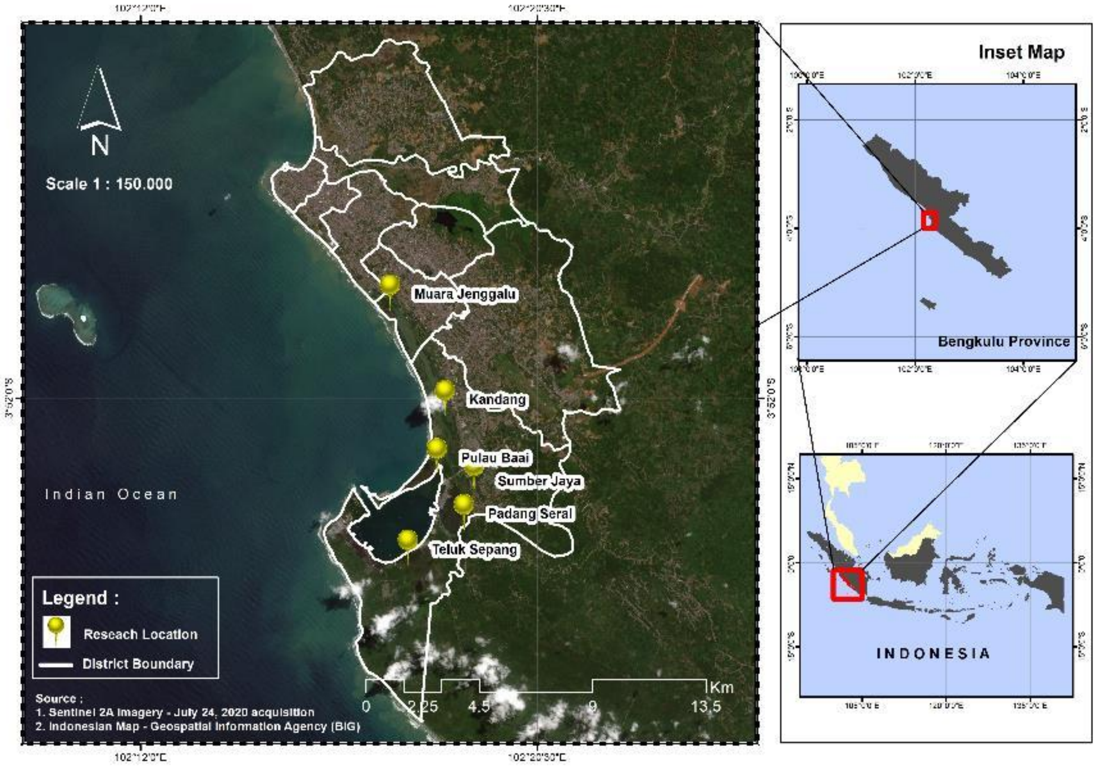

Figure 1. Study area

2.2 Data and Tools

This study used Level 2B - Sentinel satellite image acquired on August 23, 2021, and the specification of Sentinel data is shown in Table 1. The image pre-processing and spectral transformation steps are conducted by the image processing software. The NDVI was selected as the index that has been applied in various locations (Manna et al., 2014; Wachid et al., 2017) and is highly sensitive to the biomass (Purnamasari et al., 2021). GPS and tools for the ecological survey, namely tally sheet, cameras, as well as phi-band were used during the field observation.

Table 1. Data specification

Satellite	Band	Spatial Resolution (meter)	Wavelength (nm)
Sentinel-2B Acquisition time: August 23, 2021 Cloud cover: < 20%	Blue	10	490
	Green	10	560
	Red	10	665
	Near-Infrared	10	842

2.3 Image Processing

The Sentinel-2 imagery was subjected to atmospheric correction at the pre-processing stage to improve the pixel value. The reflected value of objects on the earth's surface captured by the sensor was affected because of atmospheric factors, which made the value not to be the actual pixel value. This is because the value contained is not the actual pixel value (Rumora et al., 2020). Due to scattering, the disturbance increased, while absorption reduced. The Dark Object Subtraction (DOS) technique was used to adjust for atmospheric distortion. After the atmospheric correction on the Sentinel-2B image, the mangroves area was delineated using Maximum Likelihood supervised classification (Otukei & Blaschke, 2010), among the most popular parametric classes applied in supervised learning. This algorithm can classify pixel values according to the likelihood that belongs to a particular category within the sample. Meanwhile, when the probability of the pixel value is below the specified threshold, the pixel is not classified.

The NDVI obtained from Sentinel-2B image processing was reclassified based on the actual condition from fieldwork. The field observation data and NDVI analysis were integrated to classify according to the type of mangroves density. Around 55 points (mangroves and non-mangroves) from fieldwork were occupied for accuracy tests using a confusion matrix. The accuracy test was applied to determine the reliability level of the mapping result.

2.4 Field Sample Collection

The field survey was carried out according to the guidelines for mangroves carbon estimation compiled by Kaufmann (Kauffman, 2012). A total of 140 plot samples from 6 research regions (Figure 1) were observed during the field survey. There are 85 and 55 points as training samples for the classification and validation of mapping results, respectively. The location of plot samples was mainly determined by the research purpose and accessibility. Moreover, purposive sampling was selected to accommodate area representation spatially because the research location has various land-use/land-cover surrounding mangroves areas (Vatresia et al., 2019).

The accessibility aspect was also considered and in each station, plot positions taken using GPS at the location were integrated into Sentinel-2 imagery. All plots were designed as cluster transects and consistently placed on the coastline or river body. A 10 x 10 m plot size was designed for trees, whose Diameter Breast Height (DBH) is 10 cm or above, while a 5 x 5 m was for those categorized as saplings with DBH < 10 cm (Istomo et al., 2017; Kartika et al., 2018). Ecological data, which include identifying mangroves species, distribution, and density as well as AGB data of mangroves were collected. The identification of mangroves species uses a field guide compiled in the guidebook to introduce mangroves in Indonesia (Noor et al., 2012). AGB data were obtained through allometric equations from the measurement of stem diameter circumference. This was processed to determine the estimated mangroves biomass in each plot at the research site (Komiyama et al., 2005).

2.5 Vegetation Index

Vegetation indices (VIs) are used to determine the plant density from remote sensing images. In this research, correlation and regression analysis was used to exploit the association between the values of the NDVI and the carbon information from the existing assessment to estimate the mangroves' aboveground carbon (Hastuti et al., 2017). NDVI is one of the most corresponding vegetation indices for a related purpose (Bindu et al., 2020). The NDVI expression is shown in Equation (1), while the reclassification of mangroves canopy density is presented in Table 2 based on field observations.

$$NDVI = {}^{(NIR - R)}\Big/_{(NIR + R)} \tag{1}$$

NIR : Near Infrared band (Band 8)
R : Red (Band 4)
NDVI : (-1) – (1)

Table 2. Mangroves density classification based on NDVI

No.	Category	NDVI Value
1	Rare	0.11 – 0.35
2	Medium	0.35 – 0.5
3	Dense	0.5 – 0.67

2.6 Carbon Stock Estimation

The two data on mangroves related to spatial distribution and canopy density were extracted from the Sentinel-2B image. Information on mangroves canopy density was obtained by performing the NDVI transformation. Meanwhile, in this research, the 3 classes of canopy density were rare, medium, and dense (Table 2). The NDVI transformation image produces a vegetation index value, which was visualized concerning the estimated carbon stock based on field survey data. An accuracy test was also carried out based on field data by mapping the estimated carbon stock. Mangroves forest biomass was counted using Equation (2) (Komiyama et al., 2005):

$$Wtop = 0.251 * p * DBH^{2.46} \tag{2}$$

Where Wtop represents biomass, p means bulk density; and DBH is Diameter Breast Height (cm). Furthermore, the NDVI value from satellite imagery can be used for AGB estimation using Equation (3) (Myeong et al., 2006).

$$AGB = c * e^{NDVI*d} \tag{3}$$

Where the value of c and d represent constants in the non-linear regression equation.

After obtaining the mangroves biomass estimation, the relationship between the NDVI value in the observation plot and the AGB in the field was identified. The non-linear regression equations obtained to determine the constant value of c and d were used to estimate AGB in the whole plot of the NDVI values. According to SNI 7724: 2011, 47% of tree biomass is carbon, therefore, the amount of carbon in the stock was estimated by multiplying the biomass data by the organic carbon value of 0.47.

Specifically, linear regression was used, which is the standard for evaluating statistical models for numerical data. The accuracy of carbon stock modeling based on the vegetation index was tested using the statistical method and compared to the actual observed values. The flowchart in Figure 2 depicts all the procedures for conducting this research.

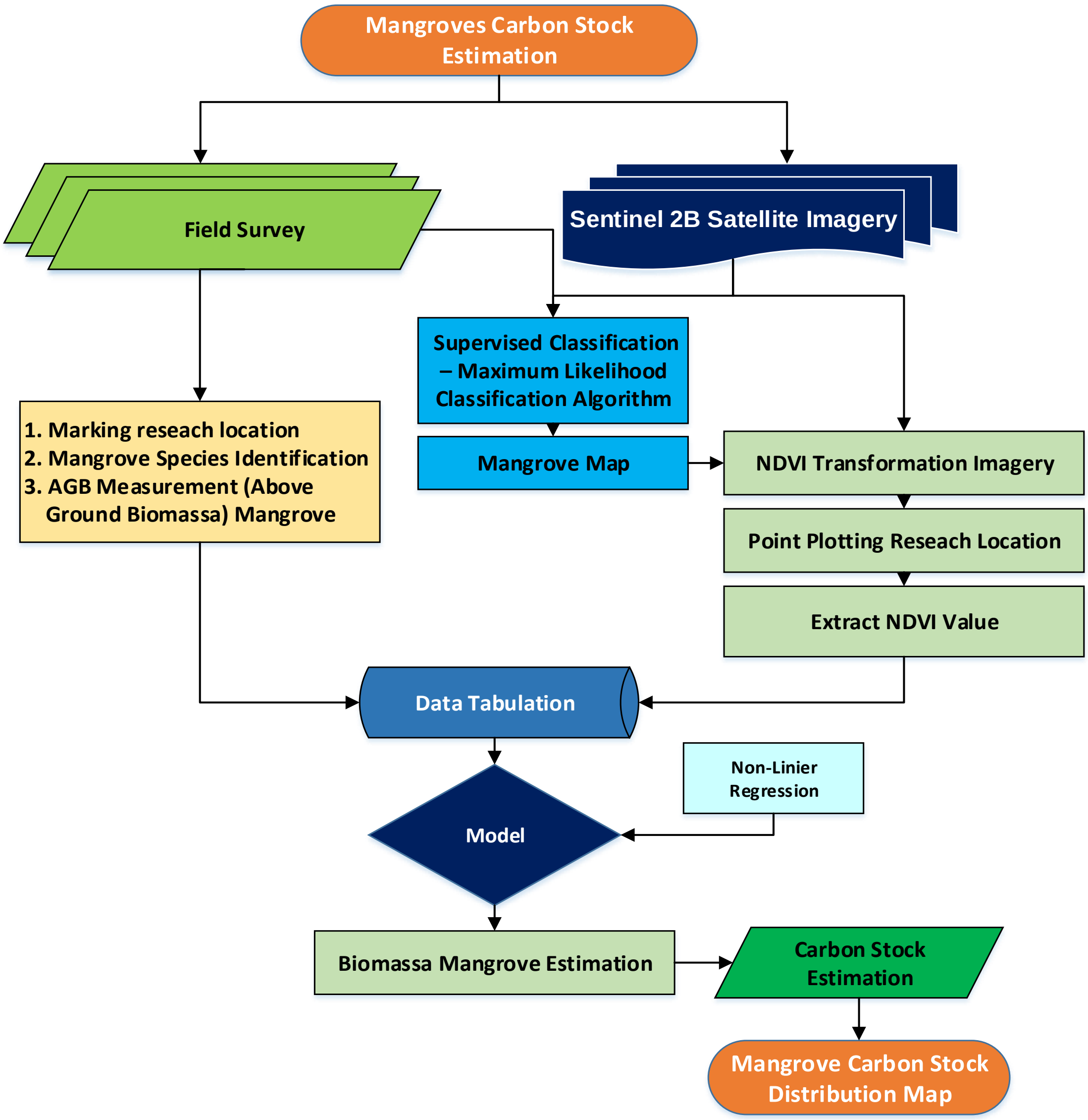

Figure 2. Workflow diagram

3. Results and Discussion

3.1 Mangroves in Bengkulu City

The supervised classification from the Sentinel 2 imagery in Figure 3 depicted the 242.35 Ha mangroves area in Bengkulu coastal, which inhabits the coastal areas of Ratu Agung, Gading Cempaka, and Kampung Melayu. The substrate types discovered along the mangroves' habitat are sand, mud, and sand mixed with mud. Furthermore, nearly identical results were found from previous research on the western side of Bengkulu, which claimed the mangroves' extent was about 214.62 Ha (Senoaji & Hidayat, 2017).

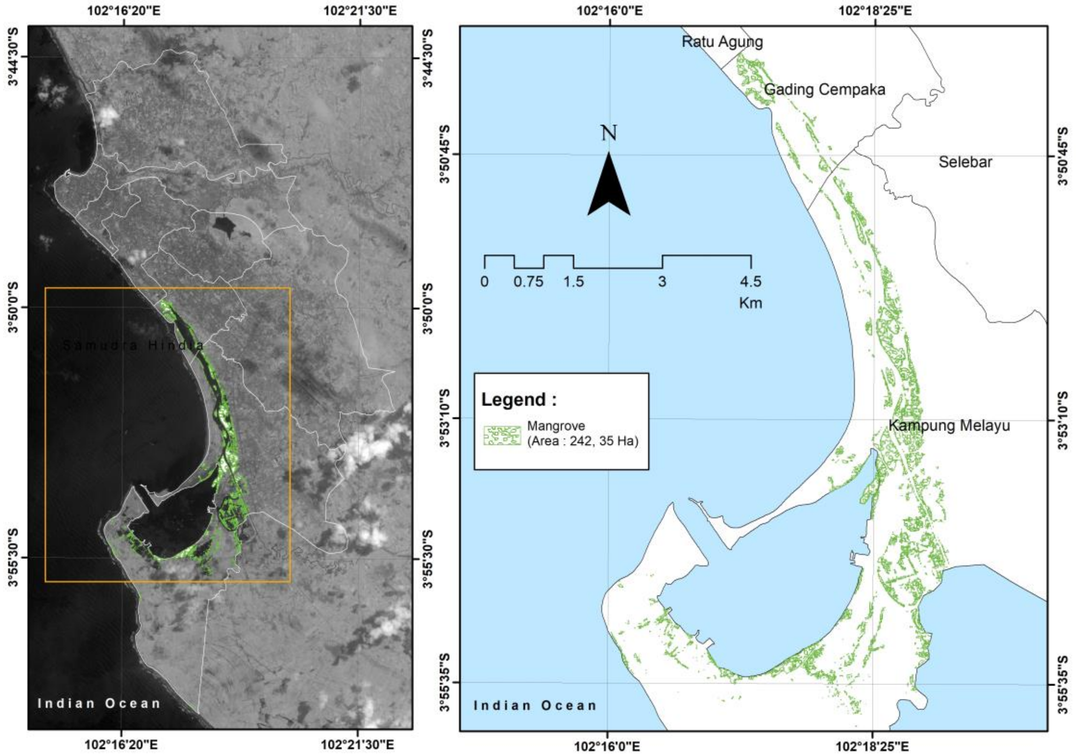

Figure 3. Mangrove distribution in Bengkulu City

Mangroves species found at the 6 survey sites are shown in Table 3, which summarizes the species data in 60 plots. It was also discovered that Rhizophora apiculata, Rhizophora stylosa, Avicennia marina, Bruguiera gymnorhiza, Ceriops tagal, Lumnitzera littorea, Lumnitzera racemosa, Sonneratia alba, and Xylocarpus granatum are the nine species that can be found in Bengkulu City. *Rhizophora apiculata* and *Avicennia marina* are the most frequently found species along the Bengkulu coast. According to a previous report, the major mangroves that dominated the city are Rhizophora, Avicennia, and Sonneratia (Apriyanto et al., 2021; Senoaji & Hidayat, 2017).

Table 3. Mangroves species in Bengkulu City

No	Species	Locations					
		A	B	C	D	E	F
1	Avicennia marina	+	+	+	+	+	+
2	Bruguiera gymnorrhiza		+	+	+	+	
3	Ceriops tagal				+		+
4	Lumnitzera littorea			+		+	
5	Lumnitzera racemose						+
6	Rhizophora apiculata	+	+	+	+	+	+
7	Rhizophora stylosa					+	
8	Sonneratia alba	+	+		+		+
9	Xylocarpus granatum	+		+			

Notes: *"+" means species mangroves found in plot sample; A – F located in TWA Pantai Panjang, Kandang, Pulau Baai, Sumber Jaya, Teluk Sepang, and Padang Serai sequentially.*

The performance of Sentinel-2 images on land-use/land-cover mapping has been long-established, and most of them reported excellent performance with the reliable accuracy result (Fathoni et al., 2017; Mondal et al., 2019; Osgouei et al., 2019; Tavares et al., 2019). To ensure that the mangroves interpretation from the Sentinel-2 image is reliable for further carbon estimation, the accuracy of the mapping result needs to reach > 80% McCoy, (2005) (Rudiastuti et al., 2021). In this case, overall (OA), producer (PA), and user (UA) accuracy was 89.09%, 89.34%, and 89.03%, respectively, with a Kappa coefficient of 0.78, as shown in Table 4.

Table 4. Accuracy assessment

Class types	Field measurements		Total	User Accuracy (%)
	M	NM		
M	23	4	27	85.19
NM	2	26	28	92.86
Total	25	30	55	
PA (%)	92	86.67		
Average UA (%)	89.03			
Average PA (%)	89.34			
OA (%)	89.09			
Kappa Accuracy (%)	78.15			

Note: *M = mangroves; NM = Non-mangroves*

Therefore, the mangroves map in Bengkulu coastal interpreted from the Sentinel-2 imagery can be used as the basis for further analysis.

3.2 Normalized Difference Vegetation Index (NDVI)

An approach such as vegetation mapping is beneficial for understanding the environmental condition. Vegetation monitoring using satellite data can use vegetation density and biomass indicators (Samsuri et al., 2021). Meanwhile, the vegetation index can estimate mangroves biomass from remote sensing images such as NDVI. The results of the NDVI transformation image and mangroves density map are available in Figure 4. The NDVI value ranged from -1 to 1, which were grouped into several density classes according to the fieldwork measurement. The relationship between the NDVI vegetation index and field measurement data can provide information about vegetation biomass (Galidaki et al., 2017). NDVI values close to zero are commonly related to the non-vegetation area (rocks and soil), while high values (positive) correspond to fractional vegetation area (Ormsby et al., 1987). In this research, the canopy density was obtained from the Sentinel-2B image using the NDVI transformation, which classified three classes of mangroves canopy density in the Bengkulu City Area. The updated information about mangrove extent using better spatial resolution images such as Sentinel-2 is essential compared to the previous results (Anggraini, 2014; Srifitriani et al., 2020). Moreover, the mangroves biomass information of Bengkulu City is vital to support ecotourism and coastal ecosystem management.

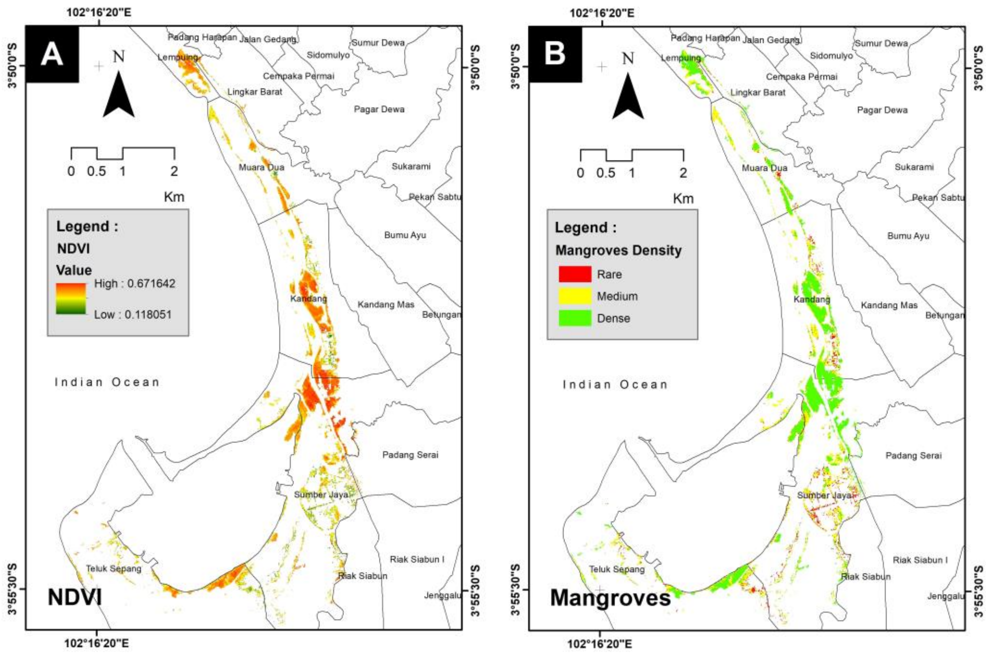

Figure 4. NDVI (a) and density classes (b) of mangroves in Bengkulu City

The mangroves distribution resulting from supervised classification was overlaid by the NDVI image in Figure 4 to determine mangroves density information. Based on Figure 4, it was discovered that mangroves with dense conditions are abundant in Kampung Melayu District. Table 5 provides an overview of the spatial extent of land covered by mangroves in Bengkulu City.

Table 5. Mangroves density within NDVI class

No.	Density class	NDVI range	Area (Ha)
1	Rare	0.11 – 0.35	21.52
2	Moderate	0.35 – 0.5	85.71
3	High	0.5 – 0.67	135.12
	Total		242.35

The vegetation index calculates the vegetation density of green leaves, specifically for vegetation species. The information about mangroves density classification and its extent in Table 5 refers to Table 2 on NDVI value classification. The three groups are mangroves areas with the highest density covering 135.12 Ha, followed by 85.71 Ha of moderate density, while rare density exists only on 21.52 ha of the total area. The NDVI range in this research is almost similar to the previous investigation. For the mangroves area on Sumatra's eastern coast, Samsuri et al. (2021) stated that an NDVI value > 0.5845 is classified as high-density mangroves. Along with what is found in mangroves in Vietnam, NDVI values from the Sentinel image vary from -0.30 to 0.66, and those with NDVI values >0.5 are classified as high density (Thuy et al., 2020). Moreover, Pricillia et al. (2021) and Singgalen et al. (2021) used a standard document from the Ministry of Environment and Forestry about the environmental damage indicators for mangroves, where it was discovered that NDVI value ≥0.4 is categorized as mangroves with high density. NDVI transformation is used in several remote sensing-based research to estimate biomass. Moreover, the research on biomass estimation using NDVI transformation in Sentinel-2 image proved the closest relationship to tree density with R = 0.738

(Samsuri et al., 2021). The efficacy of vegetation indices in assessing density is primarily determined by their responsiveness to various vegetative biochemical and biophysical features such as canopy cover, vegetation fragments, or biomass (Wicaksono et al., 2016).

3.3 Estimating the Carbon Stock in Mangroves

The model of carbon stock of mangroves in Bengkulu used the NDVI values produced from Sentinel-2B. Subsequently, the non-linear statistics regression between NDVI and AGB from fieldwork was applied to derive the constants from the carbon stock model of mangroves in Bengkulu. The regression equation was used as the basis for the carbon stock estimation to make a distribution model for the estimated distribution (Bindu et al., 2020). Figure 5 illustrates the selected field AGB and NDVI values.

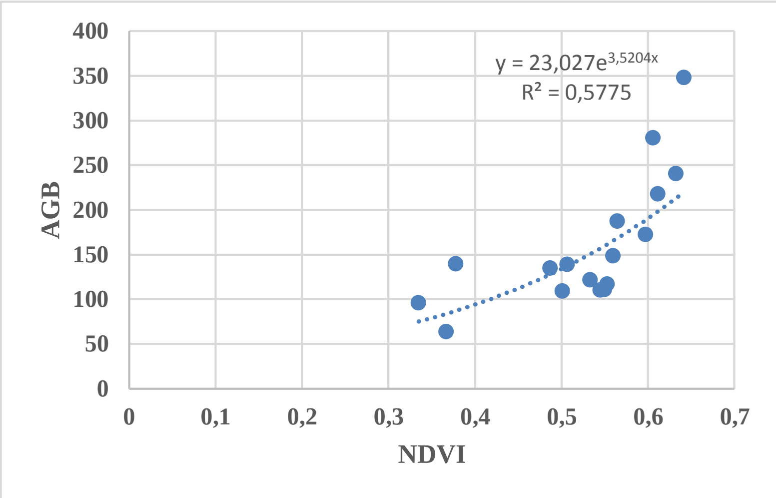

Figure 5. Correlation between AGB and NDVI models

From the statistics regression, R^2 is 0.57, and the equation $y = 23.027e^{3.5204x}$. These results indicated a positive relationship between NDVI and measured AGB. Similar research on mangroves biomass modeling in tropical Mexico, Boquilla-Mancha, using Sentinel-2 (Sjögersten et al., 2021), derived 0.57 for the R^2 value. However, Thuy et al. (2020), using a similar non-linear regression, obtained a slightly higher coefficient of determination R^2 of 0.67, while (Purnamasari et al., 2021) obtained an R^2 of 0.51 for the regression function between field-measured AGC and NDVI. The obtained number of R^2 was investigated due to the lack of field points as a reference in the model. Moreover, the spatial resolution of Sentinel-2B satellite data has an impact on the extraction of NDVI values, causing a mixture of items other than mangroves, which led to mixed values. The a and b constants for the AGB estimation model as shown in Equation (3) are 23.027 and 3.5204, respectively (Myeong et al., 2006). Therefore, the estimated AGB for mangroves in Bengkulu City is given in Equation (4).

$$\boldsymbol{AGB = 23.027e^{NDVI*3.5204}} \quad (4)$$

Equation (4) became the input for estimating the biomass from the Sentinel-2B image. Based on Figure 6, the result showed that the lowest mangroves biomass has a value of 34,8919, while the highest value was 244,965. This shows a distribution of mangroves biomass in Bengkulu City.

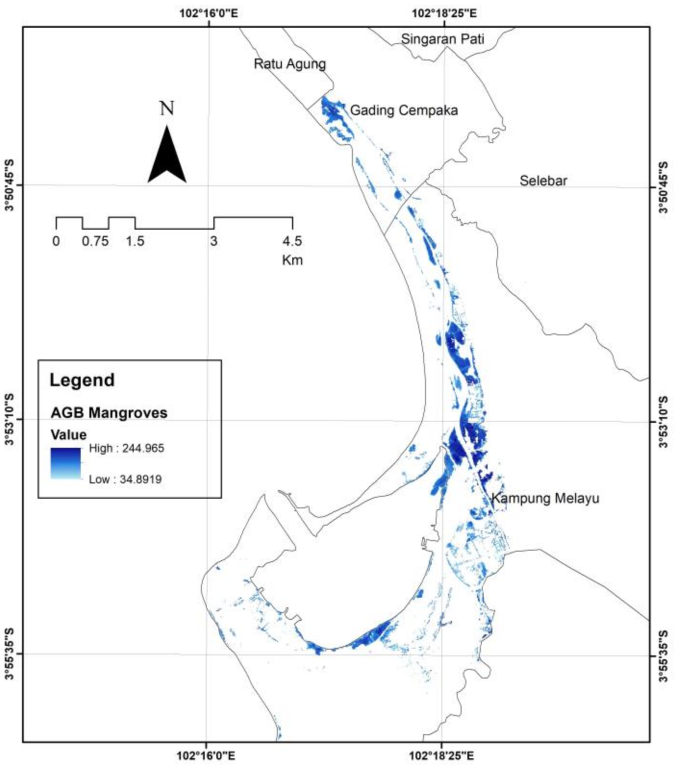

Figure 6. A map depicting the spread of mangroves biomass in Bengkulu City

After information related to mangroves biomass is obtained, the next step is to estimate carbon stock from Sentinel-2B images with the equation below:

$$\textbf{Aboveground Carbon} = \mathbf{0.47\ (23.027\ e^{(NDVI*3.5204)})}$$

Figure 7 shows a map of the mangroves' carbon stock in the Bengkulu City region. This depicts that the mangroves biomass measured from Sentinel-2B images ranges from 16.3992 t C/Ha to 115.134 t C/Ha. Similar to the value of carbon stock based on the field survey, the lowest value was 19.69 t C/Ha, while the highest was 326.06 t C/Ha. Several field plots indicate that the mangroves area is dense but contains a low NDVI value (0.11 - 0.35), and vice versa. When the field survey point indicates that the mangroves area is rare, the NDVI value is high, which ranges from 0.5 to 0.67). This contributes to the discrepancy between the estimated carbon stock calculated in the field and based on Sentinel-2B images. Some points also represent dense mangroves density values with high NDVI and low mangroves density values with low NDVI values. The field result showed that the low NDVI value is sometimes discovered in dense mangroves areas in the field plot because NDVI only detects canopy, while the field density was obtained from the DBH (Ren et al., 2015). The related condition would affect the calculation of mangroves carbon stock.

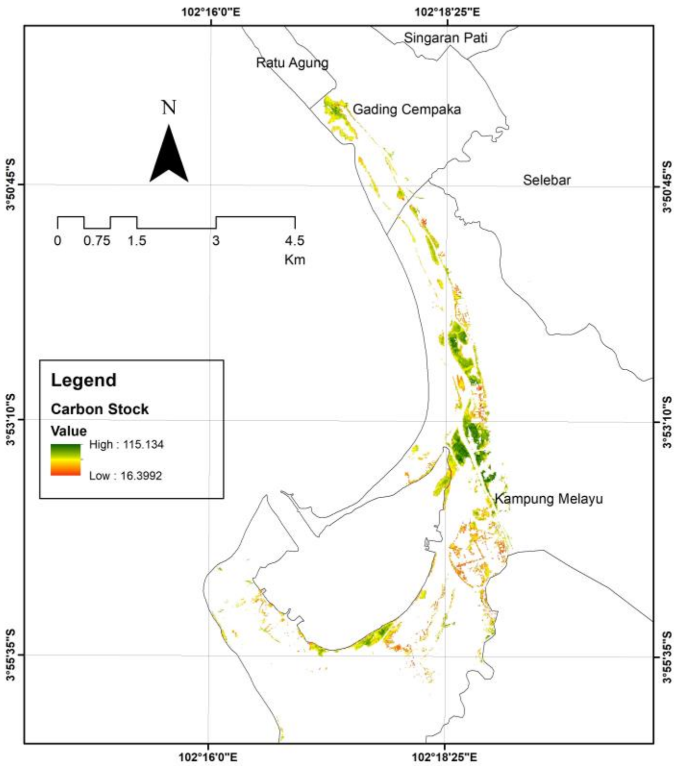

Figure 7. Carbon stock distribution of mangroves in Bengkulu City

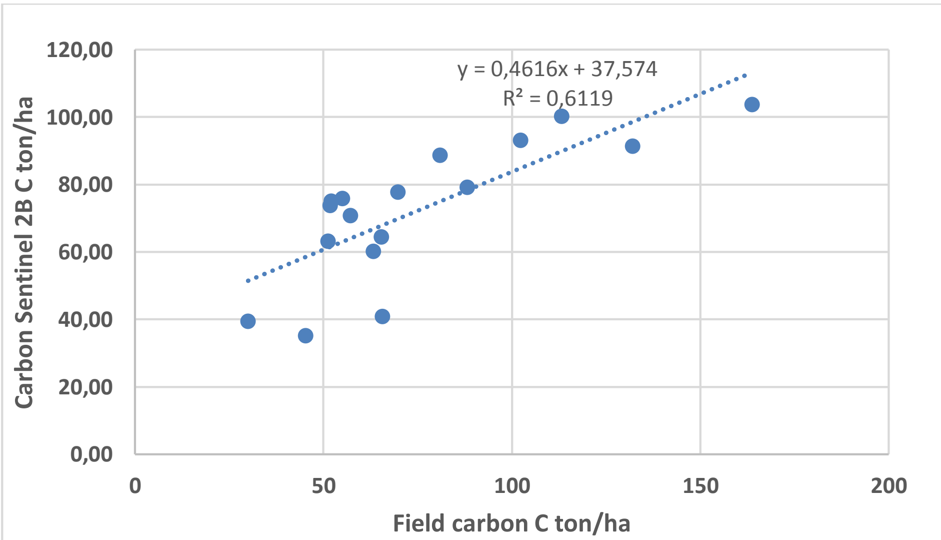

Figure 8. Regression function between measured and image-predicted carbon

Figure 8 shows how the carbon stock model derived from Sentinel 2 imagery was transformed using the NDVI to represent the actual carbon stock based on field measurement. This research discovered that Sentinel 2 imagery can be used to estimate mangroves carbon stock up to 61%. Meanwhile, Mngadi et al. (2021) implemented a random forest model to Sentinel 2 imagery to predict urban reforested carbon stock in South Africa and yielded an accuracy of 79.82 and an RMSE between 0.38 - 0.47 t/Ha. Sentinel 2 imagery data combines its resolutions, namely spatial, temporal, and spectral better than other optical datasets (Ghosh et al., 2021). However, an investigation using a goodness-of-fit statistical test discovered that all models generated inflated results when comparing field-measured aboveground carbon over several vegetation indices, such as NDVI (Purnamasari et al., 2021). This occurred because the canopy density collected by satellite sensors within the mangroves zone exceeded the tree diameter observed in the survey. Meanwhile, when ALOS AVNIR-2 PC was used to map mangroves carbon stocks in Karimun Jawa, maximum accuracy of 77.8% for aboveground carbon and 60.8% for belowground carbon was obtained (Wicaksono et al., 2016).

4. Conclusion

This study showed that Sentinel-2 imagery could be used to produce spatial information related to mangroves and estimate their carbon stock. Based on Sentinel-2 imagery analysis, the mangrove area is 242.35 Ha with an OA of 89.09%. In the study area, approximately nine species from the genera of Avicennia, Bruguiera, Ceriops, Lumnitzera, Rhizophora, Sonneratia, and Xylocarpus were discovered. The carbon stock estimation based on Sentinel-2 imagery has a value of 16.3992 – 115.134 t C Ha^{-1}, while that of field survey data ranges from 19.69 to 326.06 t C Ha^{-1}. For further investigation, multiscale mapping using several types of satellite imagery is recommended. Furthermore, high-resolution satellite image data is needed to produce detailed spatial distribution and mangroves carbon stock data.

Conflict of Interests

The authors do not have any financial, personal, or other links with other people or organizations related to the subject matter of this research, which can create a conflict of interest.

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