BIOMASS ESTIMATION MODEL AND CARBON DIOXIDE SEQUESTRATION FOR MANGROVE FOREST USING SENTINEL-2 IN BENOA BAY, BALI

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Abstract. Remote sensing technology can be used to find out the potential of mangrove forests information. One of the potentials is to be able to absorb three times more CO_2 than other forests. CO_2 absorbed during the photosynthesis process, produces organic compounds that are stored in the mangrove forest biomass. Utilization of remote sensing technology is able to detect mangrove forest biomass using the density level of the vegetation index. This study focuses on determining the best AGB model based on the vegetation index and the ability of mangrove forests to absorb CO_2. This research was conducted in Benoa Bay, Bali Province, Indonesia. The satellite image used is Sentinel-2. Classification of mangroves and non-mangroves using a multivariate random forest algorithm. Furthermore, the mangrove forest biomass model using a semi-empirical approach, while the estimation of CO_2 sequestration using allometric equations. Mean Absolute Error (MAE) is used to evaluate the validation of the model results. The classification results showed that the detected area of Benoa Bay mangrove forest reached 1134 ha (OA: 0.98, kappa: 0.95). The best AGB estimation result is the DVI-based AGB model (MAE: 23.525) with a value range of 0 to 468.38 Mg/ha. DVI-based AGB derivatives are BGB with a value range of 0 to 79.425 Mg/ha, TAB with a value range of 0 to 547.8 Mg/ha, TCS with a value range of 0 to 257.47 Mg/ha, and ACS with a value range of 0 to 944.912 Mg/ha.

Keywords: *Mangroves, remote sensing, vegetation indices, biomass, CO_2 sequestration*

1 INTRODUCTION

Mangrove forests play an important role in coastal communities and are one of the most diverse ecosystems in the world (Worthington et al., 2020; Iqbal, 2020). The current problem is deforestation and degradation of mangrove forests, it contributes to increase the concentration of carbon dioxide (CO_2) in the atmosphere (Murdiyarso et al., 2015). According to Donato et al., (2011), mangrove forests are able to absorb three times more CO_2 than other forests. For this reason, sustainable protection efforts for mangrove forests are necessary.

Obtaining information quickly related to the amount of biomass, carbon, and CO_2 absorption in mangrove forests is one of the sustainable protection efforts for local governments in making decisions. The utilization of remote sensing data is the right solution for the desired speed of information. For this reason, the best model was built using Sentinel-2 data combined with field biomass data (Heumann, 2011). Research related to the use of Sentinel-2 data for biomass and carbon information has been carried out by Sibanda et al., (2015), Castillo et al., (2017), and Pham et al., (2018), but in this study it has not been developed until information on CO_2 absorption.

Mangrove forest that has high CO_2 absorption potential is Benoa Bay mangrove. The geographical location of Benoa Bay is in the urban and tourist center of Bali Province. So it is very susceptible to damage.

The current problem of the Benoa Bay mangrove forest is the potential for damage due to the development of coastal areas in the last decade (Sugiana et al., 2022). This situation threatens to reduce the CO_2 absorption area, especially in the south of Bali Province. This study aims to determine the best model for estimating above ground biomass (AGB) based on the vegetation index and the ability of mangrove forests to absorb CO_2. Therefore, it is necessary to research information on CO_2 absorption of mangrove forests in Benoa Bay as a suggestion for local governments (especially Ngurah Rai Forest Park) so that the natural ecosystems can be maintained.

2 MATERIALS AND METHODOLOGY

2.1 Methods

Details of the Sentinel-2 data utilization method used to build the estimation information of total carbon stock and the amount of CO_2 sequestration in mangroves were schematically presented in Figure 2-1.

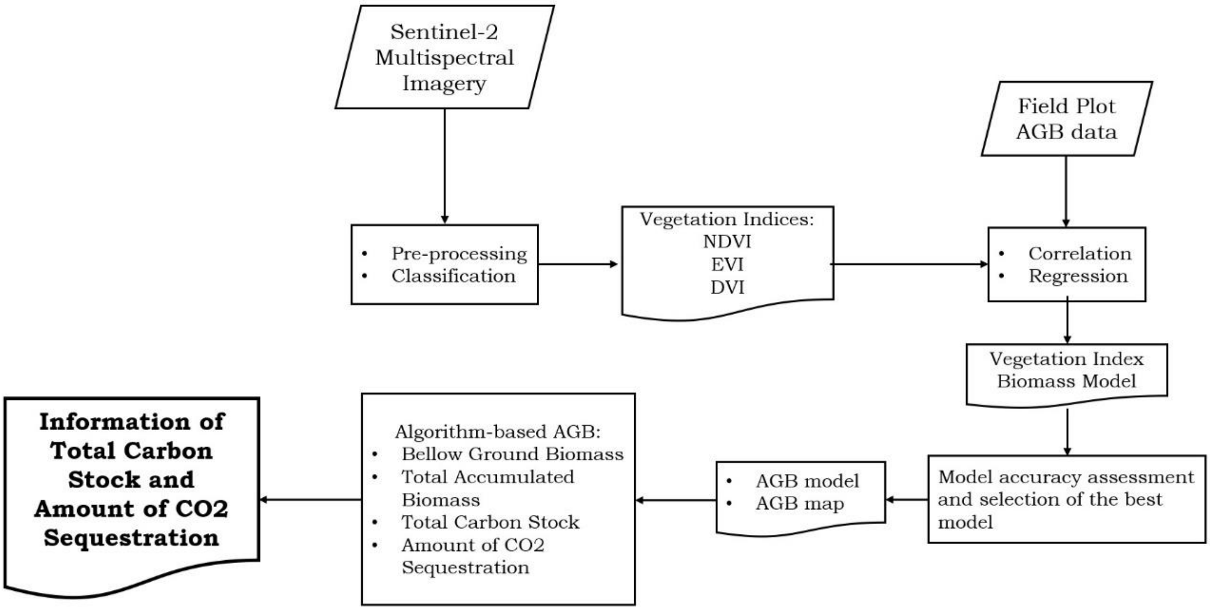

Figure 2-1: The flowchart of study methods

2.2 Location and Data

The research is located in Benoa Bay, Bali as shown in Figure 2-2. Geographically, Benoa Bay is located between 8°41'55"S to 8°48'6"S and 115°10'22"E to 115°15'12"E. Based on the Decree of the Minister of Forestry Number: 544/Kpts-II/1993 dated September 25, 1993, the area of mangrove forest in the area reaches 1,373.5 ha.

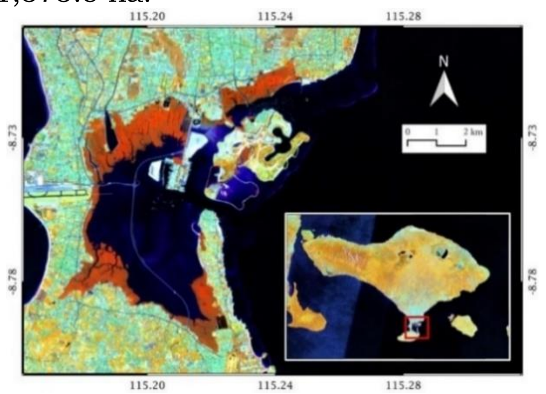

Figure. 2-2: Location of the research area from composites RGB false color (NIR, SWIR, Red)

The Data used in this research is Sentinel-2 composite (January – December 2020) cloud-free. The data was obtained from the Research Center for Remote Sensing, BRIN as the official institution in image data acquisition in Indonesia.

Furthermore, for the classification of mangroves and non-mangroves using the random forest (RF) method. Validation test using confusion matrix because it has good accuracy (Han et al., 2012).

2.3 Field Data Collection

In this study, 40 sample points were taken according to the conditions of the field. The plot size at each point was 10x10 meters. Data collection on the plot includes species identification and measurement of diameter at breast height (DBH). According to Pearson et al., (2005), DBH was measured as high as 1.3 meters (adult chest height).

2.4 Vegetation Indices

The vegetation index generated from Sentinel-2 is the basis for making an estimation model of mangrove forest biomass. The vegetation index used includes:

- Normalized Difference Vegetation Index (Rouse et al., 1973; Ramdani et al., 2018),
  $NDVI = \frac{NIR-Red}{NIR+Red}$ (2–1)
- Enhanced Vegetation Index (Huete et al., 2002),
  $EVI = G\frac{(NIR-Red)}{(NIR+C1*Red-C2*Blue+L)}$ (2–2)
  Coefficient: G: 2.5, C1: 6, C2: 7.5, L: 1
- Difference Vegetation Index (Hong-wei et al., 2019),
  $DVI = NIR - Red$ (2–3)

2.5 Above Ground Biomass (AGB)

The calculation of the AGB estimate uses an allometric equation that has been designed for Asian mangroves (Table 2-1). DBH is used in the AGB calculation input (Kumar & Mutanga, 2017). In this study, AGB was calculated for each species.

2.6 AGB Model Development

AGB estimation approach is calculated using a linear regression model with the dependent variable is AGB and the independent variable is the vegetation index

2.7 Accuracy assessment and model validation

The data is divided into 2, namely 75% for building the model and 25% for validation. The accuracy of the model uses the coefficient of determination (R^2) with the best results (> 0.8). Field data (25%) is used for validation, then Mean Absolute Error (MAE) is used in calculating the error value. The best model of the vegetation index (NDVI, EVI, DVI) is selected and the next process is carried out.

2.8 Below Ground Biomass (BGB)

After getting the estimated AGB value, then the BGB estimate can be derived using the equation developed by Cairns et al., (1997).

$BGB = exp(-1.0587 + 0.8836 * Ln(AGB))$ (2–4)

BGB = the value of bellow ground biomass (Mg/ha), AGB = the value of above ground biomass (Mg/ha).

2.9 Total Accumulated Biomass (TAB) Calculation

TAB is the total of AGB and BGB, can be calculated by the following equation:

$TAB = AGB + BGB$ (2–5)

TAB = the value of total accumulated biomass (Mg/ha)

2.10 Total Carbon Stock (TCS)

TCS can be calculated using the equation developed by Westlake, (1963) as follows:

$TCS = TAB * \%\, C\ Organic$ (2–6)

TCS = the value of total carbon stock (Mg/ha), TAB = the value of total accumulated biomass (Mg/ha), %C organic based on the rules published in the Indonesian National Standard (2011) 7724:2011, in which 0.47 or 47% of biomass is carbon.

2.11 Amount of CO_2 Sequestration (ACS)

ACS is calculated using the equation suggested by the IPCC, (2001) as follows:

$ACS = 3.67 * TCS$ (2–7)

ACS = the Amount of CO_2 Sequestration (Mg/ha), TCS = the value of total carbon stock (Mg/ha).

Table 2-1: Allometric equations used in this study to determine AGB (D is tree DBH in cm; ρ is wood density in g cm-3)

Species	Equation	Wood density (ρ)[a]
Bruguiera gymnorhiza	$0.0754 * \rho * D^{2.505}$	0.741
Rhizophora apiculata	$0.043 * D^{2.63}$	0.8814
Rhizophora mucronata	$0.128 * D^{2.60}$	0.94
Sonneratia alba	$0.3841 * \rho * D^{2.101}$	0.6443
Xylocarpus granatum	$0.1832 * D^{2.2}$	0.6721

Reference: Fromard et al., (1998) Komiyama et al., (2005), Kauffman & Cole (2010)

3 RESULTS AND DISCUSSION

3.1 Image Classification and Identified Mangrove Species

The research area is focused on Benoa Bay, Bali Province. The satellite image used is Sentinel-2 composite (January – December 2020) cloud-free. The mangrove area found was 1134 ha. The validation test results obtained are Overall Accuracy (OA) of 0.98 with a kappa coefficient of 0.95.

The species found at the research site were *Rhizophora apiculata*, *Rhizophora mocrunata*, *Sonneratia alba*, *Xylocarpus granatum*, and *Bruguiera gymnorhiza*. The dominant species was *Rhizophora sp.*, this is in accordance with the statement of Cerón-Souza et al., (2010), namely *Rhizophora sp.* mostly found in tropical coastal areas.

3.2 AGB Image-estimated and predictive mapping

The vegetation index describes the greenness of the vegetation object. The higher the value of the vegetation index, the higher the level of greenness of the object being observed, and vice versa. In this study, the vegetation index used has a different range of values: NDVI = 0.24 to 0.91, EVI = 0.06 to 0.9, DVI = 0.02 to 0.54. To ensure the data is suitable for use in the next process, a normality test is carried out.

Table 3-1 presents the results of the normality test with 40 data inputs (Figure 3-1). The amount of data is in accordance with the samples collected in the field. The results show Dn < KS_{table}, therefore these data meet the assumptions of parametric statistical research.

Table 3-1: The Kolmogorov–smirnov normality test results.

Input	Statistic		
	Mean	**Dn**	**KS_{table}**
AGB observed	174.6	0.085	0.210
NDVI	0.715	0.074	0.210
EVI	0.443	0.043	0.210
DVI	0.273	0.059	0.210

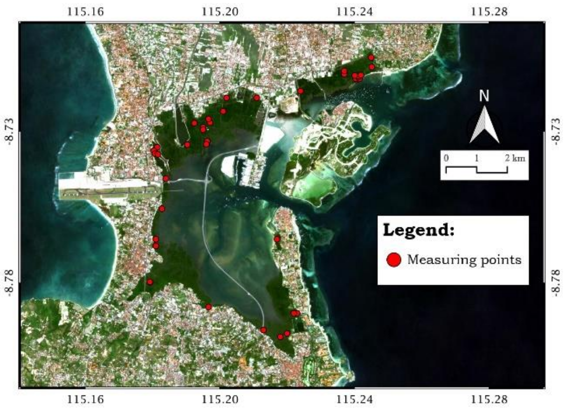

Figure 3-1. Field condition and measuring points

Based on the Kolmogorov–smirnov normality test results, concluded that the estimated data were suitable for use in statistical analysis. The correlation test showed DVI (0.876) has the strongest relation with field measured AGB, as compared to NDVI (0.823) and EVI (0.875).

After the data is declared feasible to use, then a linear regression analysis was performed to determine the AGB estimation model. Based on the results shown in Figure 3-2, the DVI has a higher R^2 (0.7679) compared to NDVI (0.677) and EVI (0.766). This shows that the pixel value generated from DVI can describe 76.79% of the variation in AGB measured in the field.

The model based on linear regression equation with the best R^2 is $y = 900.47x-18.234$ where y is the AGB in the field and x is the DVI value. The three vegetation indices tested in this study shows a strong relation between the x and y variables. The model results are then applied to the AGB estimation (Figure 3-2), then a validation test is carried out so that the best model can be continued to the next process.

Based on Figure 3-3, it is the distribution pattern of the estimated AGB of each model based on the vegetation index (NDVI, EVI, and DVI). It can be seen that the distribution pattern of AGB in the north of the study site is higher than in the south. The same pattern was also found by Mahasani et al., (2021). NDVI-based AGB has a value range of 0 to 285.8 Mg/ha, EVI-based AGB has a value range of 0 to 410.52 Mg/ha, and DVI-based AGB has a value range of 0 to 468.38 Mg/ha.

3.3 AGB maps accuracy assessment

Furthermore, a validation test is carried out on the model based on the vegetation index (NDVI, EVI, and DVI). Figure 3-4 shows the pattern of relations between model-based AGB estimates and AGB field observations. Where EVI-estimated-AGB and DVI-estimated-AGB have a strong relation, because the data distribution pattern is closer to the dotted line compared to the NDVI-estimated-AGB data distribution.

Mean Absolute Error (MAE) is used to strengthen the results in Figure 3-4. The lower the MAE value, the higher the accuracy. The MAE calculation results (Table 3-2) show that the NDVI-based model has an error value of 35.482 Mg/ha, the EVI-based model has an error value of 25.545 Mg/ha, and the DVI-based model has an error value of 23.525 Mg/ha. DVI produces the lowest error value, meaning that DVI-based AGB has high accuracy.

Table 3-2: Comparison of the vegetation indices used in this research.

Input	r	R^2	MAE
NDVI	0.823	0.677	35.482
EVI	0.875	0.766	25.545
DVI	0.876	0.7679	23.525

DVI proved to be effective for the detection of the estimated AGB of mangrove forests. This result is also supported by the research of Wicaksono et al., (2016) and Purnamasari et al., (2021). DVI is effective because it has a simple formula, is consistent at all radiometric levels, and is able to improve the vegetation aspect. The use of the red band is able to absorb chlorophyll well and the use of the NIR band has a high reflectance.

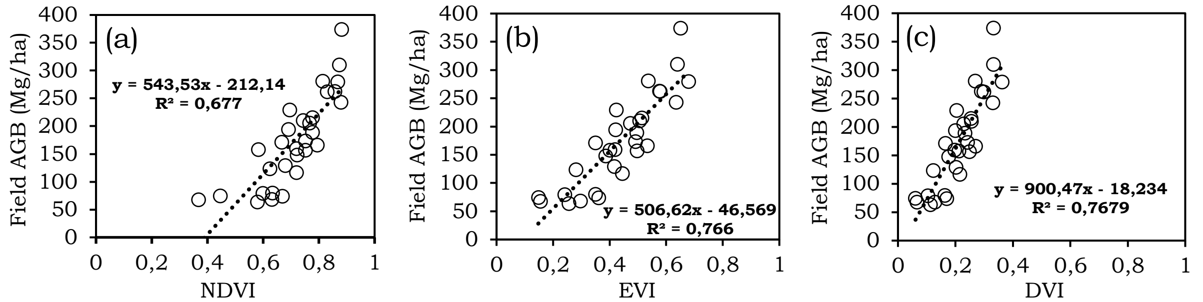

Figure 3-2: Regression function between field-measured AGC and (a) NDVI, (b) EVI, and (c) DVI

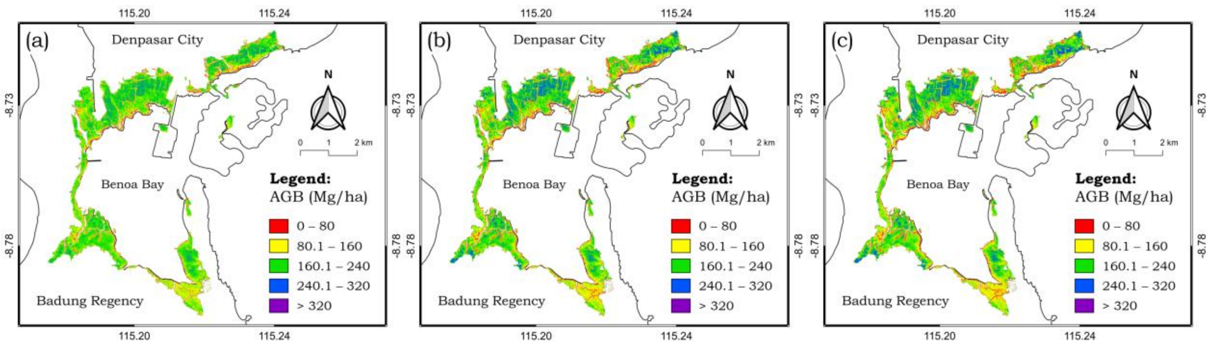

Figure 3-3: Predicted maps of AGB distribution in the study site derived from vegetation indices model, (a) NDVI, (b) EVI, and (c) DVI

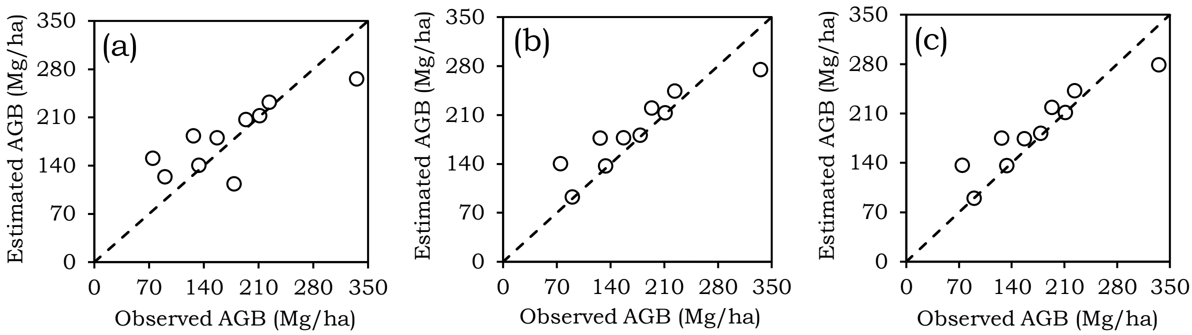

Figure 3-4: The 1:1 goodness-of-fit plot of field-measured AGB against (a) NDVI-estimated AGB, (b) EVI-estimated AGC, and (c) DVI-estimated AGC

3.4 Mangrove Biomass Mapping

After obtaining the DVI as the best vegetation index in the estimation of AGB of mangrove forests, then the BGB estimation is calculated using equation 2-4. Mangrove BGB is biomass in roots (axial and fine roots), rhizomes, and leaf litter (Craft, 2013; Fourqurean et al., 2019). The processing results shown that the BGB value was lower than AGB. The range of BGB values in this study was 0 to 79.425 Mg/ha. This is in accordance with the results by Hastuti et al., (2017) in Jembrana, Bali. The difference in AGB and BGB values was determined by mangrove species, geographical location, canopy density, and ecology factors (Sahu et al., 2016). The spatial distribution of BGB can be seen in Figure 3-5.

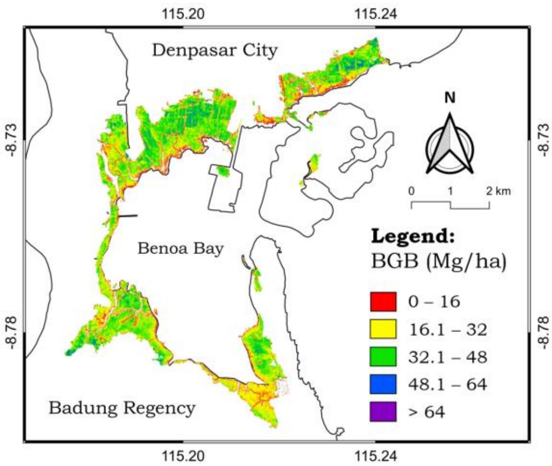

Figure 3-5: Distribution of below-ground biomass (BGB) derived DVI (Eq. 2-4) in the study site

Furthermore, the estimated values of AGB and BGB are added together to produce an estimate of the total biomass at the study site (TAB). The range of TAB values in this study was 0 to 547.8 Mg/ha. The spatial distribution of TAB can be seen in Figure 3-6.

In this study, there is a positive relation between DVI-based AGB estimation and BGB estimation. These results indicate that BGB can be estimated using AGB (Meng et al., 2021). The use of remote sensing technology is highly recommended in obtaining BGB information through AGB.

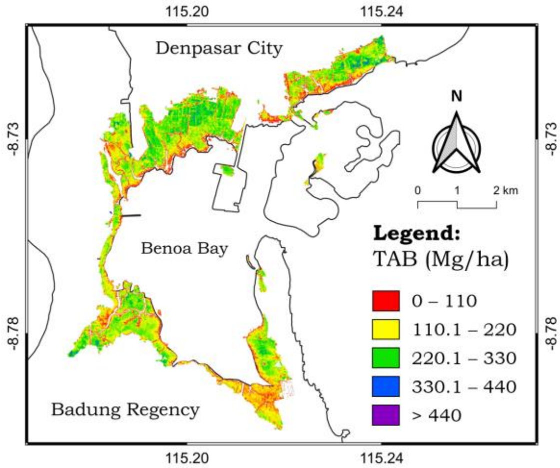

Figure 3-6: Distribution of total accumulated biomass (TAB) derived DVI (Eq. 2-5) in the study site

3.5 Total Carbon Stock and CO_2 Sequestration Mangrove Mapping

The estimated TAB value that has been calculated can then be reduced to an estimated total carbon stock (TCS) using equation 2-6. 47% of plant biomass is carbon (Indonesian National Standard (SNI), 2011; Fourqurean et al., 2019). The range of TAC values in this study was 0 to 257.47 Mg/ha. The spatial distribution of TCS can be seen in Figure 3-7.

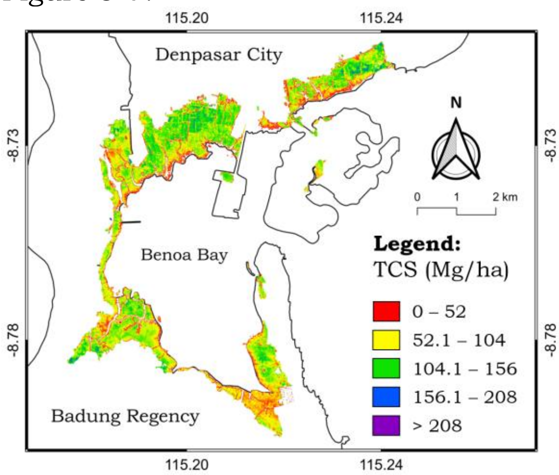

Figure 3-7: Distribution of total carbon stock (TCS) derived TAB (Eq. 2-6) in the study site

The spatial distribution pattern of the estimated TCS of the Benoa Bay mangrove forest is in accordance with the results of field observations. High TCS (dominated by *Rhizophora sp.*) was found in the dense mangrove canopy.

Meanwhile, low TCS values (dominated by *Sonneratia sp.*) were found in the sparse mangrove canopy. These results are in accordance with the research conducted by Wirasatriya et al., (2022) with the research location in Karimunjaya Islands. These results are also reinforced by several studies which state that there is a positive relation between the canopy and TCS of mangrove forests (Jones et al., 2014; Benson et al., 2017).

After getting the TCS value, the last step of this research is to derive equations 2-7 so as to produce the amount of CO_2 sequestration (ACS). ACS of mangrove forests is the ability of mangrove ecosystems to absorb CO_2 (Matthews et al., 2021). The range of ACS values for mangrove forests in this study was 0 to 944.912 Mg/ha.

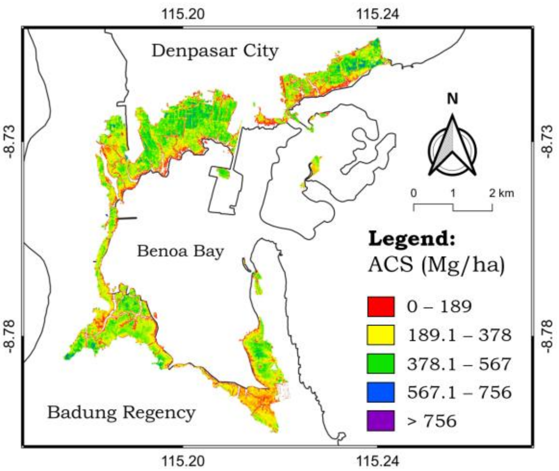

Figure 3-8: Distribution of amount of CO_2 sequestration (ACS) derived TCS (Eq. 2-7) in the study site

Plant biomass (mangroves) are closely related to the photosynthesis process (Tarakanov et al., 2022; Abideen et al., 2022). The absorption of CO_2 from the photosynthesis process produces organic compounds, so that the plant biomass increases. The higher the tree diameter (Imani et al., 2017) and tree height (Fu & Wu, 2011), the higher the plant's ability to absorb free carbon from the air.

Furthermore, to improve the results of this study, models can be developed using other vegetation indices, combining vegetation indices, and improving the level of accuracy. Allometric algorithm for estimation of CO_2 absorption can be developed further. So that the level of accuracy in the estimation of biomass, carbon, and CO_2 absorption of mangrove forests can increase.

4 CONCLUSIONS

In this study, the classification of mangrove objects using the multivariate random forest algorithm had good results (OA: 0.98, kappa: 0.95, area: 1134 ha). Overall, the utilization of the vegetation index based on Sentinel-2 satellite imagery has potential in estimating mangrove forest biomass. Based on the results of the model in this study, the DVI vegetation index has good accuracy in the estimation of AGB (r: 0.876, R^2: 0.7679, MAE: 23.525) with a value range of 0 to 468.38 Mg/ha. Furthermore, the DVI-based AGB model can be derived using allometric equations to produce BGB (0 to 79.425 Mg/ha), TAB (0 to 547.8 Mg/ha), TCS (0 to 257.47 Mg/ha), and ACS (0 to 944.912 Mg /Ha). The use of the DVI-based on AGB model is very relevant in estimating the carbon stock of mangrove forests, as well the model can be used in estimating CO_2 sequestration of mangrove forests.

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AUTHOR CONTRIBUTIONS

Author 1: conceptualization, field survey, methodology, investigation, visualization and writing the original draft, Author 2: methodology, investigation, field survey, visualization and writing the original draft, Author 3: methodology, investigation, field survey, visualization and writing the original draft, Author 4: methodology, field survey, investigation, visualization and writing the original draft, Author 5: Methodology, field survey, and investigation, Author 6: reviewing the writing, and editing the finalized manuscript, Author 7: methodology, investigation, field survey, and writing the original draft, Author 8: reviewing the writing and editing the finalized manuscript, Author 9: reviewing the writing and editing the finalized manuscript, Author 10: reviewing the writing and editing the finalized manuscript.

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