ESTIMATION OF MANGROVE CARBON STOCK WITH HYBRID METHOD USING IMAGE SENTINEL-2

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ABSTRACT: Field survey data combined with remote sensing data were an ideal and practical method for estimating carbon stocks. The objective of this research was to get an estimation model of mangrove carbon stock with good accuracy. Modeling used hybrid methods, by combining satellite image analysis and field data. The result of this research was to get the mangrove carbon estimation model. Model 1 merging between NNIP vegetation index equation using regression of power/geometry and six variables multiple regression (NDRE or WVVI vegetation index, sediment depth, soil density, % C soil depth 0-15 cm, 15-50 cm and >50 cm). RMSE test resulted 0.4778 t 100 m -2 and % RMSE 16.12%. Model 2 NNIP vegetation index and three variable regression (VIRRE vegetation index, sediment depth, soil density). RMSE test resulted 0.5639 t 100 m -2 and % RMSE 19.03%. Model 3 uses NNIP vegetation index and two variable regression (NDRE vegetation index and sediment depth). RMSE test resulted 0.7295 t 100 m -2 and % RMSE 24.63%. Model 4 incorporation of NNIP vegetation index and multiple regression of 3 variables (VIRRE vegetation index, average sediment depth value 100.63 cm, soil density value 1.02 g cm-3). RMSE test resulted 1.0043 t 100 m -2 and % RMSE 33.89%.

Keywords: Mangrove biomass, Carbon stock, Sentinel-2 Imagery, Hybrid

1. INTRODUCTION

Mangroves could absorb carbon better than terrestrial ecosystems because of its ability to bury carbon in sediments [1]; Estimation of mangrove biomass by field survey combined with remote sensing data was an ideal and practical method [2]. The assessment of carbon stocks with remote sensing was expected to reduce destructive ways or mangrove destruction. The estimated share of mangrove carbon with remote sensing imagery has been done using various images, such Quickbird [3], ALOS, Landsat [4], and, RADARSAT [5]. Different types of mangroves showed significant differences in the spectral reflection of the electromagnetic spectrum. High spatial resolution images could map full carbon stocks at the mangrove species level [6].

The use of remote satellite sensing to measure the spread of biomass and mangrove carbon provided accurate, efficient, and repeatable information. Some vegetation indices such Vegetation indexes such as DVI (Difference Vegetation Index), EVI (Enhanced Vegetation Index), and MRE-SR (Modified Red Edge-Simple Ratio) with field data to estimate carbon stock [6]. The objective of the study was to obtain a mangrove carbon stock model and its accuracy using Sentinel-2 satellite images.

This survey is a continuation of a study conducted by Muhsoni et al. (2018). This study focuses on obtaining estimation models of mangrove carbon stock by a hybrid method using the Sentinel-2 image. This study can contribute to the easier estimation of mangrove carbon stock in a region more quickly and efficiently with better accuracy.

2. MATERIALS AND METHODS

2.1. Satellite Remote Sensing Data

Mangrove mapping can use Sentinel-2 satellite images (Copernicus Sentinel data (2017)). The Sentinel-2 satellite had 13 spectral bands from near-infrared to shortwave infrared. Spatial resolution varied from 10m - 60m depending on spectral band [7]. Sentinel 2 image used in this research was December 6, 2016. The channels used in this study were band 2, 3, 4, 5, 6, 8, 8a.

2.2. Pre Processing

Sentinel-2 imagery performed radiometric correction at an early stage. The radiometric correction uses the at-sensor reflectance method by changing the pixel value to the at-sensor radiance. Then converted to at-sensor reflectance [8], [9]. Mangrove area obtained by hybrid method NDVI
using threshold value from NDVI. The automatic thresholding method used was Otsu Threshold [10].

2.3. Mangrove Carbon Stock Model with Hybrid Method.

Model estimates of mangrove carbon by separating carbon and soil carbon biomass. Carbon biomass modeling (stems, roots, bottom plants) with vegetation index using nonlinear regression approach. Soil carbon estimate uses the hybrid method. Then sought the model with the best accuracy (least RMSE test).

Utilization of vegetation index in remote sensing for mapping related to vegetation [11]. Index of vegetation used 24 indexes (BR, GNDVI, GR, SAVI, MSAVI, NDRE, NDVI, NDVI2, NDWI, NNIP, PSRI, RR, VIRE, SVI, VIRE, VIRRE, MTV1, MTV2, RDVI, VARI, VI green, MSR, and TVI ). The best equation has the highest coefficient of determination ($R^2$) and the lowest RMSE [9], [6], [13], [14]. The regression equation used was [12]:

- **Exponential**: $Y = a \times e^{bx}$ (1)
- **Logarithmik**: $Y = a + b \times \ln(x)$ (2)
- **Polynomial**: $Y = a + bx + cx^2$ (3)
- **Power/geometrik**: $Y = a \times x^b$ (4)

The final model with the hybrid method, by combining two approaches that use image and field measurement data [13]. This modeling performed several simulations:

- Model 1 with inputs of vegetation index values, sediment depth, soil density and % soil carbon.
- Model 2 with inputs of vegetation index values, sediment depth, and density.
- Model 3 with inputs of vegetation index values and into the soil.
- Model 4 with input only vegetation index.

2.4. Test Accuracy with RMSE.

Accuracy tests used correlation coefficient ($r$) and Root Mean Square Error (RMSE) [14], [15], [16], [17], [5]. Equation:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (x_i - y_i)^2}$$ (5)

$$RMSE \% = 100 \times \frac{RMSE}{\bar{Y}}$$ (6)

Where: $x_i$ = Value The carbon stock of the measurement, $y_i$ = the predicted value of the carbon stock, $\bar{Y}$ = the mean carbon measured [18], [19], [20], [21], [22], [23], [24], [25].

2.5. Study Area

Research location was in Pesisir Selatan district of Pamekasan, East Java, Indonesia. The number of measuring stations were 11, and each station had ten plots (Fig 1). The total plot number as the sample location sample location were 110 plots.

![Fig. 1 Map of Research Location](image)

3. RESULTS AND DISCUSSION

Initial stages of the study involved radiometric correction of the Sentinel-2 image. Radiometric correction by converting radian value to at-sensor reflectance. Daoedoro et al. (2015) described this method as proving better and most stable for carbon stock estimation [26], [6].

The results of field measurements on all plots were analyzed, obtained carbon biomass and soil carbon data. Data tested, data test with Kolmogorov-Smirnov normality test [9]. The result of statistical analysis of Kolmogorov-Smirnov normality test obtained values $>0.05,$

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3.1. Modeling Estimation of Total Carbon Mangrove Content (Carbon Biomass and Soil Carbon) with Value of Vegetation Index

The initial phase of total estimation of mangrove carbon was carried out with non-linear regression of total carbon (carbon biomass and soil carbon) with Sentinel 2 image vegetation index value (24 species of vegetation index). The coefficient of determination ($R^2$) showed a weakly correlated result if $R^2 <0.5$ [27], [28], [29], [30], [14], [31]. The result of determination value with regression exponential, logarithmic, polynomial and power/geometry got value $R^2 <0.5$ (value $R^2$ biggest 0.064). The value of $R^2$ shows the regression between total mangrove carbon and vegetation index is not feasible because of the weak correlation value.

3.2. Biomass Carbon Content Estimation Modeling.

The result of determining regression value of exponential, logarithmic, polynomial and power/geometry between a variable of carbon biomass with vegetation index get a value of $R^2$ was having a good/reliable correlation (value $R^2 >0.8$). Regression was having values of $R^2 >0.8$, exponential regression for vegetation index NDVI, NDVI2, NNIP, SVI, MTV2, RDVI, MSR; regression of power/geometry for vegetation index of GNDVI, NDVI, NDVI2, NNIP, SVI, RDVI, MSR (Table 1). SPOT 5 and Landsat TM images obtained the best vegetation index was NDVI with non-linear regression [32], [5]. Worldview-2's best index is DVI, EVI, MRE-SR with allometric equations and 80.9% accuracy [6]. This result differed from this research. The best vegetation index was NNIP (Normalized Near Infrared with power equation/geometry with RMSE value 0.2474 t 100 m$^2$).

Table 1 RMSE test results and model of the Sentinel 2 image biomass estimation equation

| No | Regression of vegetation index | Carbon Biomass Model |
|----|--------------------------------|---------------------|
| 1  | NNIP power                      | $y = 280.44519x^{13.63868}$ |
|    | RMSE = 0.2470 t 100 m$^2$, $R^2 = 0.8570$ |         |
| 2  | NNIP exponential               | $y = 0.0000004e^{22.258846x}$ |
|    | RMSE = 0.2490 t 100 m$^2$, $R^2 = 0.8528$ |         |
| 3  | GNDVI power                     | $y = 66.76199x^{6.22939}$ |
|    | RMSE = 0.2498 t 100 m$^2$, $R^2 = 0.8696$ |         |

| No | Regression of vegetation index | Carbon Biomass Model |
|----|--------------------------------|---------------------|
| 4  | NDVI power                      | $y = 20.16317x^{8.33372}$ |
|    | RMSE = 0.2523 t 100 m$^2$, $R^2 = 0.8696$ |         |
| 5  | NDVI2 power                     | $y = 20.16317x^{8.33372}$ |
|    | RMSE = 0.2523 t 100 m$^2$, $R^2 = 0.8696$ |         |
| 6  | SVI power                       | $y = 20.16317x^{8.33372}$ |
|    | RMSE = 0.2523 t 100 m$^2$, $R^2 = 0.8696$ |         |
| 7  | MSAVI exponential              | $y = 0.000002e^{13.18280x}$ |
|    | RMSE = 0.2523 t 100 m$^2$, $R^2 = 0.8692$ |         |
| 8  | RDVI power                      | $y = 24.08576x^{0.04895}$ |
|    | RMSE = 0.2523 t 100 m$^2$, $R^2 = 0.8697$ |         |
| 9  | NDVI exponential               | $y = 0.00008e^{13.68111x}$ |
|    | RMSE = 0.2528 t 100 m$^2$, $R^2 = 0.8689$ |         |
| 10 | NDVI2 exponential              | $y = 0.00008e^{13.68111x}$ |
|    | RMSE = 0.2528 t 100 m$^2$, $R^2 = 0.8689$ |         |
| 11 | SVI exponential                | $y = 0.00008e^{13.68111x}$ |
|    | RMSE = 0.2528 t 100 m$^2$, $R^2 = 0.8689$ |         |
| 12 | MSR power                       | $y = 0.07086x^{4.6446}$ |
|    | RMSE = 0.2536 t 100 m$^2$, $R^2 = 0.8687$ |         |
| 13 | RDVI power                      | $y = 0.00075e^{12.28222x}$ |
|    | RMSE = 0.2542 t 100 m$^2$, $R^2 = 0.8672$ |         |
| 14 | MSAVI power                     | $y = 24.25246x^{9.74722}$ |
|    | RMSE = 0.2562 t 100 m$^2$, $R^2 = 0.8696$ |         |
| 15 | MSR exponential                | $y = 0.00326e^{3.28180x}$ |
|    | RMSE = 0.2571 t 100 m$^2$, $R^2 = 0.8595$ |         |

Description: $X =$ Vegetation Index Value, $n$ (RMSE) = 80.

ALOS AVNIR-2 image was EVI-2, TVI, ARVI, SAVI, and MSAVI. The MSAVI vegetation index with exponential equations provided the smallest or most accurate standard of error, with above-ground carbon averages of 0.2582-0.5968 t 100 m$^2$ [8]. Kamal (2015) obtained for the best Worldview-2 SAVI vegetation index image with RMSE 1.15, for the best model ALOS AVNIR-2 NDVI vegetation index with RMSE 1.31, for Landsat TM image of the best vegetation index SR with RMSE 1.23 [21]. Muhsoni et al. (2018) obtained an appropriate vegetation index for estimation of estuarine mangrove biomass was the NDVI vegetation index with 0.089 t 100 m$^2$ RMSE [33].
3.3. Soil Carbon Content Estimation Modeling.

Soil carbon modeling with soil carbon calculation equation \((C_t = K_d \times \rho \times \% \text{organic C})\). Here, \(K_d\) is depth of soil / sediment (cm), \(\rho\) is density of action (g cm\(^{-3}\)) and \(\% \text{C}\) is % of C depth 0-15 cm, 15-50 cm and >50 cm. The equation of the modeling result is:

\[ Y = ((15 \times x_1 \times x_2) + (35 \times x_1 \times x_3) + ((x_5 - 50) \times x_1 \times x_4)) \]

Description: \(x_1\) is bulk density (g cm\(^{-3}\)), \(x_2\) is % C depth 0-15 cm, \(x_3\) is % C depth 15-50 cm, \(x_4\) is % C depth >15 cm, \(x_5\) is sediment depth (cm). The RMSE test results for this model was 0.5039 t 100 m\(^2\).

Soil carbon modeling with regression of soil carbon with vegetation index with exponential, logarithmic, polynomial, power/geometric and linear regression got determination value \(R^2 < 0.5\) (the most significant \(R^2\) value 0.209). The amount of \(R^2\) found that all regression models between soil carbon and vegetation index are not feasible to use because they have a weak correlation.

Soil carbon modeling with multiple regression using several simulations:

1. Regression equation with two variables, namely \(X_1\) = vegetation index value, and \(X_2\) = sediment depth.
2. Regression equation with 3 variables, namely \(X_1\) = vegetation index value, \(X_2\) = sediment depth and \(X_3\) = bulk density.
3. Regression equation with 6 variables, namely \(X_1\) = vegetation index value, \(X_2\) = sediment depth, \(X_3\) = bulk density, \(X_4\) = % C depth 0-15 cm, \(X_5\) = % C depth 15-50 cm and \(X_6\) = % C depth >15 cm.

The result of model got a coefficient value of determination of multiple regression with six variable got value 89.8%-90.7%, showed very good regression. Multiple regression with three variables got the value of determination 52.8% - 58.7%, The value showed good enough regression. Regression of 2 variables got a determination value of 32.8% -37.8%, showed poor regression. Regression of 6 variables, three variables and two variables that had the highest determination value 4 was the vegetation index VIRE, VIRRE, WVVI, and NDRE.

The RMSE test result for the best six variable modeling used NDRE (Normalized difference Red-Edge index) value of RMSE 0.5011 t 100 m\(^2\) and WVVI (WorldView Improved Vegetative Index) vegetation index of RMSE 0.5011 t 100 m\(^2\) value. Multiple modeling for the three highest RMSE test variables were VIRE vegetation index with RMSE 0.5924 t 100 m\(^2\) and VIRRE vegetation index equation with RMSE 0.934 t 100 m\(^2\). Multiple modeling for two highest variables using NDRE vegetation index equation with RMSE 0.7747 t 100 m\(^2\) and WVVI vegetation index equation with RMSE 0.7747 t 100 m\(^2\).

3.4. Determination of Best Model of Total Mangrove Carbon Content

The determination of the total mangrove carbon content model was done by combining the biomass carbon estimation model with the soil estimate model. In this modeling some simulations were performed:

1. Model 1 with equation 1-1:

\[ y = (280.44519*(X_1)^{13.63868}) + (-3.42587-3.44731\times X_2 + 0.01795\times X_3 + 2.81797\times X_4 + 25.45099\times X_5 + 17.43371\times X_6 + 50.02014\times X_7) \]

Description: \(X_1\) = NNIP vegetation index, \(X_2\) = NDRE vegetation index, \(X_3\) = NIR1-band 8, \(X_4\) = band 4, \(X_5\) = band 3, \(X_6\) = band 5, \(X_7\) = Depth of sediment (cm), X4 = bulk density (g cm\(^{-3}\)), \(X_5\) = % C depth 0-15 cm, \(X_6\) = % C depth 15-50 cm, \(X_7\) = % C depth >15 cm. RMSE=0.47786 t 100 m\(^2\), % RMSE=16.12%, Mean=2.84 t 100 m\(^2\), Std=0.59 t 100 m\(^2\), Min=1.39 t 100 m\(^2\), Max=5.47 t 100 m\(^2\), Total Carbon mangrove=187,398.0 t C, Average C ha\(^{-1}\) = 283.61 t C ha\(^{-1}\) (Fig. 2).

Equation 1-2:

\[ y = (280.44519*((X_1)^{13.63868})) + (-3.42587-3.44731\times X_2 + 0.01795\times X_3 + 1.52865\times X_4) \]

Description: \(X_1\) = NNIP vegetation index, \(X_2\) = VIRRE vegetation index, \(X_3\) = NIR1-band 8, \(X_4\) = band 4, \(X_5\) = band 3, \(X_6\) = band 5, \(X_7\) = Depth of sediment (cm), X4 = bulk density (g cm\(^{-3}\)), \(X_5\) = % C depth 0-15 cm, \(X_6\) = % C depth 15-50 cm, \(X_7\) = % C depth >15 cm. RMSE=0.47786 t 100 m\(^2\), % RMSE=16.12%, Mean=2.85 t 100 m\(^2\), Std=0.69 t 100 m\(^2\), Min=1.28 t 100 m\(^2\), Max=9.11 t 100 m\(^2\), Total Carbon mangrove=187,790.3 t C, Average C ha\(^{-1}\) = 284.20 t C ha\(^{-1}\) (Fig. 3).

2. Model 2 with the equation:

\[ y = (280.44519*((X_1)^{13.63868})) + (3.08347-1.7259\times X_2 + 0.01640\times X_3 + 1.52865\times X_4) \]

Description: \(X_1\) = NNIP vegetation index, \(X_2\) = VIRRE vegetation index, \(X_3\) = NIR1-band 8, \(X_4\) = band 4, \(X_5\) = band 3, \(X_6\) = band 5, \(X_7\) = Sediment depth (cm), X4 = bulk density (g cm\(^{-3}\)), \(X_5\) = % C depth 0-15 cm, \(X_6\) = % C depth 15-50 cm, \(X_7\) = % C depth >15 cm. RMSE=0.47786 t 100 m\(^2\), % RMSE=16.12%, Mean=2.86 t 100 m\(^2\), Std=0.69 t 100 m\(^2\), Min=1.39 t 100 m\(^2\), Max=5.47 t 100 m\(^2\), Total Carbon mangrove=187,790.3 t C, Average C ha\(^{-1}\) = 284.20 t C ha\(^{-1}\) (Fig. 3).
total Carbon mangrove = 194,301.0 t C, Average C ha\(^{-1}\) = 294.05 t C ha\(^{-1}\) (Fig. 4).

### 3. Model 3 with the equation:

\[ y = (280.44519 \times (X1)^{3.63868}) + (3.34631 - 7.78604 \times X2 + 0.02042 \times X3) \]

Description: 
- \( X1 = \text{NNIP vegetation index} \)
- \( X2 = \text{NDRE vegetation index} \)
- \( \text{NNIP} = \frac{NIR1}{(NIR1 + R + G)} \)
- \( \text{NDRE} = \frac{NIR1 - RE}{NIR1 + RE} \)
- \( \text{NIR1} = \text{band 8}, \ R = \text{band 4}, \ G = \text{band 3}, \ RE = \text{band 5}, \ X3 = \text{Depth of sediment (cm)} \)
- \( \text{RMSE} = 0.7295 \ t \ 100 \ m^2, \ % \text{RMSE} = 24.63\% \)
- \( \text{Mean} = 3.29 \ t \ 100 \ m^2, \ \text{Std} = 0.73 \ t \ 100 \ m^2, \ \text{Min} = 1.23 \ t \ 100 \ m^2, \ \text{Max} = 6.38 \ t \ 100 \ m^2 \)
- Total Carbon mangrove = 216,574.4 t C, Average C ha\(^{-1}\) = 327.76 t C ha\(^{-1}\) (Fig. 5)

### 4. Model 4 with the equation:

\[ y = (280.44519 \times (X1)^{3.63868}) + (3.08347 - 1.7259 \times X2 + 0.01640 \times X3 + 1.52865 \times X4) \]

Description:
- \( X1 = \text{NNIP vegetation index} \)
- \( X2 = \text{VIRRE vegetation index} \)
- \( \text{NNIP} = \frac{NIR1}{(NIR1 + R + G)} \)
- \( \text{VIRRE} = \frac{NIR1}{RE} \)
- \( \text{NIR1} = \text{band 8}, \ R = \text{band 4}, \ G = \text{band 3}, \ RE = \text{band 5}, \ X3 = \text{average sediment depth} \ (100.63 \ cm), \ X4 = \text{average density of action} \ (1.02 \ g \ cm^{-3}) \)
- \( \text{RMSE} = 1.0043 \ t \ 100 \ m^2, \ % \text{RMSE} = 33.89\% \)
- \( \text{Mean} = 3.2 \ t \ 100 \ m^2, \ \text{Std} = 0.44 \ t \ 100 \ m^2, \ \text{Min} = 1.073 \ t \ 100 \ m^2, \ \text{Max} = 5.05 \ t \ 100 \ m^2 \)
- Total Carbon mangrove = 210,619.7 t C, Average C ha\(^{-1}\) = 318.75 t C ha\(^{-1}\) (Fig. 6).

The ALOS AVNIR-2 image obtained the best vegetation index for above ground carbon was EVI1 with error 22.9% and for underground carbon index of GEMI vegetation with 40% error [26]. These results were different from those produced in this study. Compared to this research, this study obtained better accuracy with an error of 16.2%.

### 4. CONCLUSION

The best modeling of Sentinel-2 for estimation of mangrove carbon is model 1. Model 1 with the merging of NNIP vegetation index equation using the power/geometric regression for biomass carbon estimation and six variable regression (NDRE or WVVI vegetation index, sediment depth, soil density, % C depth 0-15 cm, % C depth of 15-50 cm and % C depth >50 cm). RMSE test resulted in 0.4778 t 100 m\(^2\) and RMSE % of 16.12%. Model 2 estimates of biomass using NNIP vegetation index and soil carbon estimate using multiple regression of 3 variables (VIRRE vegetation index, sediment depth, soil density). RMSE test result was 0.5639 t 100 m\(^2\) and RMSE 19.03 %. Model 3 biomass estimation using NNIP vegetation index and soil estimate using two variables (NDRE vegetation index and sediment depth). RMSE test result was 0.7295 t 100 m\(^2\) and RMSE 24.63%. The four merger model between the NNIP vegetation index equations uses the power/geometric regression for biomass carbon estimation and the three variable multiple regression (VIRRE vegetation index, average sediment depth value 100.63 cm, 1.02 g cm\(^{-3}\) soil density). RMSE test result is 1.0043 t 100 m\(^2\) and % RMSE 33.89%.
Fig. 3 Map of mangrove carbon and histogram table results Model 1-2.

Fig. 4 Map of mangrove carbon and histogram table results Model 2.

Fig. 5 Map of mangrove carbon and histogram table result of Model 3.
Fig. 6 Map of the mangrove carbon and histogram table result of Model 4.

5. ACKNOWLEDGMENTS

The author would like to thank the doctoral program of Fishery and Marine Science Faculty of Brawijaya University, Indonesia. The Sentinel-2 image used is a product of Copernicus Sentinel Data, the European Space Agency (ESA).

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