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Mapping Mangrove Surface Carbon Stocks Using Multisensor Imagery in Clungup Mangrove Conservation (CMC) Malang Regency

Maulana Abdul Hakim[1*], Muhammad Kamal[2], Sanjiwana Arjasakusuma[2]
[1]*Magister Penginderaan Jauh, Fakultas Geografi, Universitas Gadjah Mada, Yogyakarta, Indonesia*
[2] *Departemen Sains Informasi Geografi, Fakultas Geografi, Universitas Gadjah Mada, Yogyakarta, Indonesia*

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Corresponding Author
E-mail:
maulana.abdul.hakim@mail.ugm.ac.id

ABSTRACT

Mangroves can store carbon effectively with a value of about 1,023 Mg C/Ha and become one of the richest forests that store 4-20 billion tons of blue carbon globally. Remote sensing imagery can be used to map mangrove surface carbon stocks using radar and optical image sensors. Generally, forest carbon on earth is stored in two places, namely above the surface (Above Ground Carbon, AGC) and below the surface (Below Ground Carbon, BGC). This study aims to estimate the surface carbon stock of mangroves using multisensory imagery using the Random Forest method in the Clungup Mangrove Conservation (CMC) area, Malang Regency, East Java. Four vegetation indices (IRECI, NDI45, NDVI, SAVI), single band, and VV VH polarization were used as predictive variables. Estimating the carbon stock mangrove value using Sentinel-1 imagery produced 2,126 tons of C with R^2 0.11. Meanwhile, Sentinel-2 produces an estimated carbon value of 2,025 tons C with an R^2 of 0.22. The estimation model using Sentinel-2 shows a better evaluation value with a Root Mean Squared Error (RMSE) of 0.89 and a Mean Absolute Error (MAE) of 0.75. The IRECI vegetation index is the most important variable in estimating carbon stocks. The results of the mapping accuracy of the Sentinel-1 model show a value of 34.73% and Sentinel-2 35.03%.

INTRODUCTION

Vegetation is a controller in efforts to reduce carbon emissions in the atmosphere, one of which is mangroves. Indonesia is one of the countries that has the longest coastline, so mangrove ecosystems grow throughout the Indonesian archipelago (Yuniastuti et al., 2012). Mangroves can reduce greenhouse gas emissions and mitigate climate change because they can filter pollutants and absorb carbon dioxide (CO_2) released into the atmosphere (Pham et al., 2019).

Generally, forest carbon on earth is stored in two places, namely above the surface (Above Ground Carbon, AGC) and below the surface (Below Ground Carbon, BGC). Mangroves can store carbon more effectively than other vegetation with a value of around 1,023 Mg C / Ha, so mangrove ecosystems are considered one of the richest forests capable of storing 4-20 billion tons of blue carbon globally (Donato et al., 2011).

Information on carbon absorption in mangroves is very important to obtain as input in mangrove conservation and management efforts. Remote sensing is a technological innovation that can accurately and measurably assess the condition of the earth's surface. One of them is calculating forest carbon stocks using satellite imagery data. Using satellite imagery has the advantage of monitoring a large area geographically, time efficiency, high accuracy, and effectiveness in measuring biomass in large forest areas (Pham et al., 2018).

The mangrove surface carbon stocks can be calculated using optical and radar imagery data. Visual imagery data is widely used for surface carbon estimation because it has several advantages, namely high spatial resolution, multispectral channels, and multi-temporal data. So that from these data, various methods such as single channel analysis and index transformation can be applied to obtain accurate results even though they are limited by constraints on atmospheric effects (Alan et al., 2017; Kamal et al., 2016).

On the other hand, radar imagery has the advantage of being able to penetrate the clouds so that recording can be carried out at any time. This imagery effectively overcame atmospheric disturbances, especially in tropical regions. However, it is limited to the number of channels and has a wide recording scope, so special techniques are needed for its use (Su et al., 2016; Taylor & Lu, 2007).

Based on the advantages and disadvantages possessed by optical and radar imagery data, this study tried to compare the multisensor imagery data of Sentinel-1 (radar) and Sentinel-2 (optics) to predict the value of mangrove surface carbon stock. Sentinel-1 and Sentinel-2 images have the potential for mangrove observations, namely with 13 multispectral channels with three red edge channels sensitive to vegetation and cross-polarization of VV VH radar data related to vegetation structure (Alan et al., 2017; Ananto et al., 2019).

Optical imagery can estimate mangrove surface carbon stocks through spatial modelling. Many studies have been carried out to predict AGC using parametric methods, namely regression equations and non-parametric methods, namely machine learning (Nuthammachot et al., 2020; Vafaei et al., 2018).

The random forest algorithm is one machine learning technique that can create models without relying on the distribution of data used and a fast computing system (Breiman, 2001). Previous studies using machine learning have proven effective for spatial modelling of mangrove surface carbon stocks and can improve model accuracy compared to parametric methods (Heumann, 2011; Lu et al., 2016). So, the purpose of this study is to estimate the carbon stock of mangrove surfaces using multi-censor images of Sentinel-1 and Sentinel-2 using random forest algorithms.

RESEARCH METHODS

Study Area

The research area is located in Clungup Mangrove Conservation (CMC) Malang Regency, East Java, under the management of the Bhakti Alam Sendang Biru Foundation (Figure 1). CMC is located in Sendang Biru hamlet, Tambakrejo village, Sumbermanjing Wetan district. The study location is located in a geographical area with coordinates 112 ° 38' - 112 ° 43' BT and eight ° 26' - 8 ° 30' LS with a CMC area is ± 81 Ha and a coastal border covering an area of ± 117 Ha, with the main vegetation being mangroves and mixed gardens.

The CMC area has a variety of mangrove species, so it has a high potential to store large amounts of carbon. In addition, the study area has a unique landform because of the karst landform, so there are hills or domes surrounding mangroves, and it is a conservation area that has recovered from the threat of land degradation so that the ecosystem is protected. In summary, the flow of this study can be seen in figure 2.

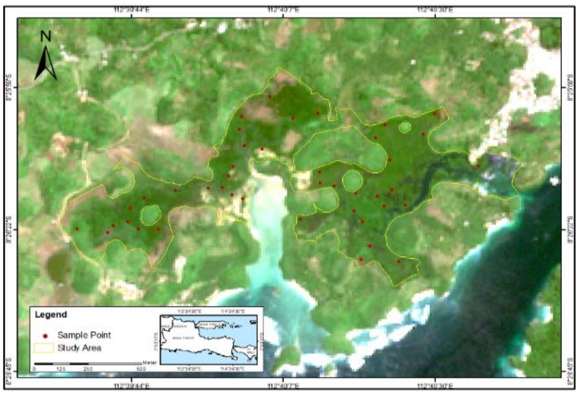

Figure 1. Map of Research Location and Plot Position of Field Samples

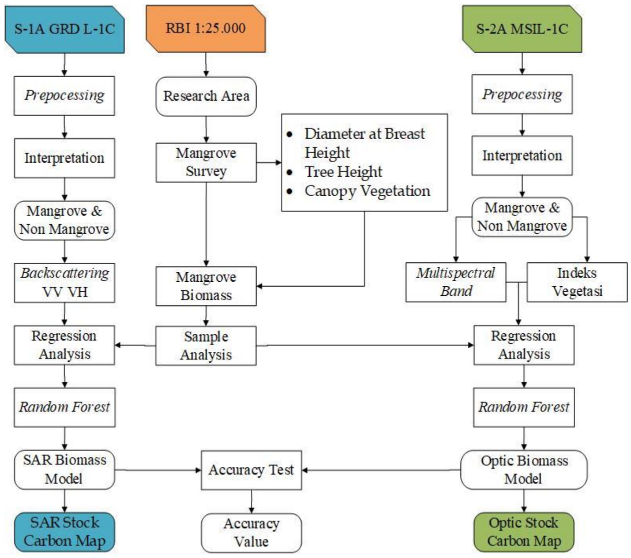

Figure 2. Research Framework

Field Data

Field sample data collection was carried out in October 2021 in 39 evenly distributed sample plots determined based on the purposive sampling method. The sample plot size is 20 m x 20 m, following the spatial resolution of the imagery. Measurements of Diameter at Breast Height (DBH), tree height, and vegetation canopy density were performed to determine the actual biomass value using a common allometric equation developed by (Komiyama et al., 2005).

Determining location coordinates is carried out with the Global Navigation Satellite System (GNSS) receiver. Position measurement uses the average waypoint method or calculates the middle coordinate position at the size time for 5 minutes to minimize the plotting error of the sample plot coordinates. The distribution of field sample points can be seen in Figure 1.

Data Processing

Sentinel-1 and Sentinel-2 imagery data used in this study are free to access through https://scihub.copernicus.eu/. Sentinel-2 imagery data is at level 1C while Sentinel-1 is at ground range detected high resolution (GRDH) level, which was acquired on September 22, 2021. Image data processing uses Sentinel Application Platform (SNAP) software developed by the European Space Agency (ESA). Sentinel-2 image processing by utilizing the Sen2cor plugin, which will automatically perform radiometric corrections from the top of atmosphere (TOA) level to the bottom of atmosphere (BOA) to eliminate the influence of sensor errors when recording images on the earth's surface (Pflug et al., 2016).

For Sentinel-1 imagery, data processing is carried out through several stages: geometric correction, speckle filtering, terrain correction, and radiometric correction. The geometric and radiometric correction of the image uses the range doppler terrain correction method to correct the image's position according to the earth's surface. Lee filter with window size 5x5 is used to reduce the effect of spots from flat radar (Filipponi, 2019). Calibration of the image using sigma nought and gamma nought. Furthermore, the last stage is converting the DN value (digital number) into dB units (disable) which is the backscatter coefficient.

It is necessary to process radiometric corrections on the imagery to adjust the spectral reflection value of the image pixels to the spectral reflection of the corresponding object. The radiometric correction process is divided into two stages: radiometric calibration to convert the digital number (DN) value into reflectant value and atmospheric correction to minimize the effect of atmospheric additives (Danoedoro, 1996).

The imagery data used in the resampling became 20 m. The transformation of 4 vegetation indices on Sentinel-2 images and single-channel reflectance were used as variables for mangrove surface carbon stock estimation. Meanwhile, the prediction variables from radar data utilize VV VH polarization. For more details on the prediction variables of mangrove carbon stocks can be seen in Table 1.

Table 1. Mangrove Carbon Stock Prediction Variables

Images	Variable Prediction
Sentinel-2	$\mathrm{IRECI} = \frac{\mathrm{NIR} - \mathrm{R}}{\mathrm{RE/RE}}$
	$NDVI = \frac{\mathrm{NIR} - \mathrm{R}}{\mathrm{NIR} + \mathrm{R}}$
	$\mathrm{NDI45} = \frac{\mathrm{RE} - \mathrm{R}}{\mathrm{RE} + \mathrm{R}}$
	$\mathrm{SAVI} = \frac{\mathrm{NIR} - \mathrm{R}}{\mathrm{NIR} + \mathrm{R} + \mathrm{L}} \mathrm{x}\, 1 + \mathrm{L}$
	B2, B3, B4, B5, B6, B7, B8, B8A
Sentinel-1	VV VH

Note:
NIR = Near Infrared RE= Red Edge
L = Optimal Value 0,5 R = Red

Mangrove Carbon Stock Modeling

The spatial model of mangrove surface carbon stocks is produced using machine learning algorithms using the random forest (RF) method. The RF method has advantages with a non-heavy computational load, thus creating a model based on the classification results of the decision tree. The division of data samples is randomly derived from observational data, so it does not affect the number of variables and values used. Three parameters must be optimized in the use of RF to get good results, namely tree (amount of data), number of regression trees, and try (number of different predictors tested (Mutanga et al., 2012).

Carbon Estimation Model Accuracy

Carbon stock estimation models need to be evaluated to compare the performance of the models obtained. The RMSE (root mean square error) method is used to assess the results of a prediction model because it can distinguish observation data and predicted data (Byrd et al., 2014). RMSE can determine the magnitude of the margin of error and evaluate the performance of the created model as a whole (Arjasakusuma et al., 2020). The RMSE calculation can be seen in equation 1.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(yi - \tilde{y}i)^2}{n}} \quad \text{......................(1)}$$

Note:
Yi: actual data value
ỹi: prediction data value
n: the amount of data

RESULT AND DISCUSSION

Sentinel-1 Carbon Estimation

The estimation of carbon values using Sentinel-1 radar data obtained results of 15 tons C / Ha and a maximum of 37.5 tons C / Ha. The total carbon value in the study area is 2,126 tons C. Spatially, the map of the estimated model results can be seen in Figure 3. The relationship between the predicted results in predicting the carbon value of image data can be explained through the coefficient of determination (R^2).

In this study, the low correlated R^2 value of 0.11 means that Sentinel-1 data can only affect 11% of surface carbon estimates, while other variables influence the remaining 89%. The low correlation value of radar data can be affected by saturation in the vegetation canopy, making radar wave sensitivity weak in predicting biomass (Ananto et al., 2019).

Other research (Ghosh & Behera, 2018) using Sentinel-1 data also obtained low R^2 value results due to the C-Band's ability to penetrate the canopy. The backscattering from the radar can only penetrate the canopy and upper branching of the vegetation, so the sensitivity is lost and affects the value of the carbon estimation.

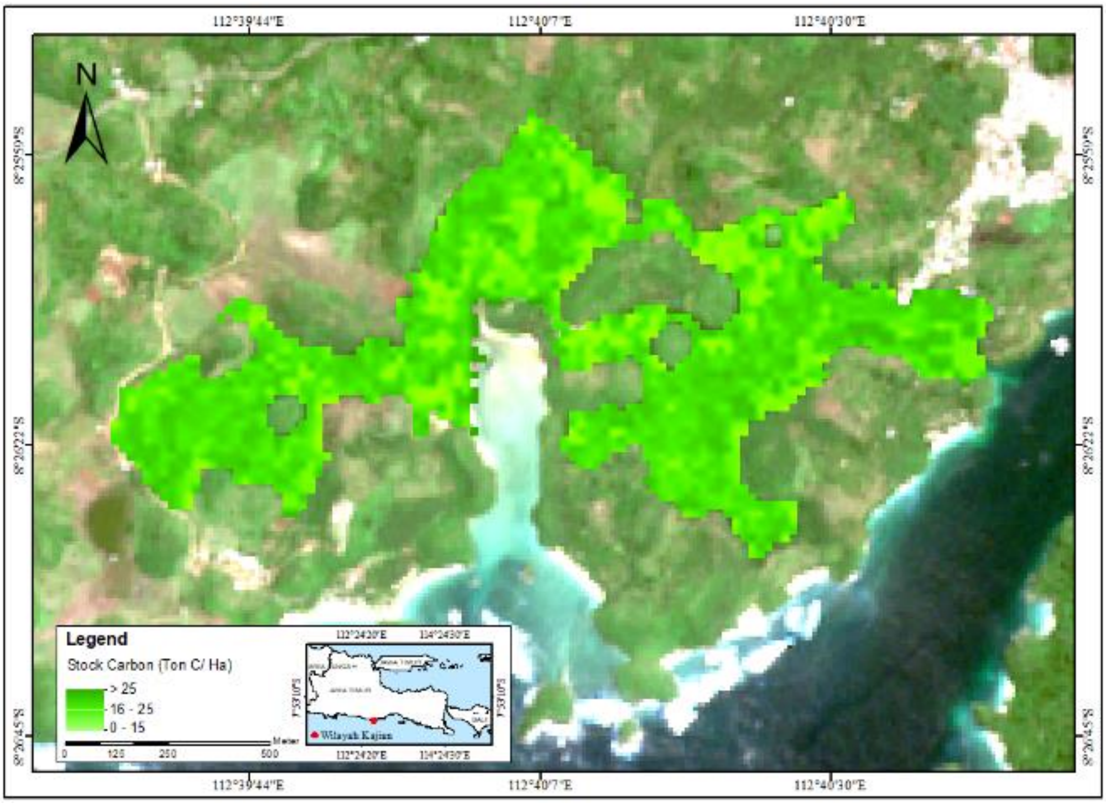

Figure 3. Model Map AGC Sentinel-1

VV polarization plays more of a role in estimating carbon than VH polarization. VV polarization is more sensitive to scattering volumes from the ground and water parts. In the study area, there are areas with low vegetation density, so the scattering of signals from soil surface roughness is more dominant (Laurin et al., 2018). The results of the study conducted by (Omar et al., 2017) also showed that the polarization of VV is more influential than VH with a low correlation value, namely $R^2 = 0.091$. Meanwhile, VH polarization plays a role in estimation due to the scattering volume of biophysical vegetation, such as branching and leaves at the level of surface roughness.

Sentinel-1 radar data in this study has not shown a good correlation between the predicted carbon and the carbon from the field. This can be influenced by several factors, such as limited data polarization, the effect of C-band wavelengths that have low penetrating power on the canopy, and backscatter from the ground and saturated mangrove areas. In addition, the influence of vegetation density in the study area can affect the predicted value, and the backscattering effect on the soil greatly affects forest areas with low density (Of et al., 2013).

Sentinel-2 Carbon Estimation

The analysis of mangrove surface carbon stock estimates using Sentinel-2 optical data get a minimum value of carbon reserves, namely 10 tons C / Ha and a maximum of 40 tons C / Ha. The total value of the overall carbon stock is 2,025 tons C. This value is lower than the previous study (Mahyatar, 2021), getting a total surface carbon stock value of 3,635.17 tons C using WorldView-2 high-resolution imagery. A more spatially clear map of the AGC model results can be seen in Figure 4.

A high spatial resolution would better present the object's state on the earth's surface. The difference in the predicted value of carbon stocks can be influenced by the characteristics of the data and the methods used. WorldView-2 imagery has a higher spatial resolution of 2 m compared to the spatial resolution of Sentinel-2 images, which is 20 m, so the number of image pixels used will be more than the lower resolution.

The value of the determination relationship between the predicted carbon and the predicted result gets a correlation value of R^2, which is 0.22. The correlation value explains that Sentinel-2 imagery data can only affect 22% of mangrove surface carbon estimates, while other variables influence more than 78%. In this study, the IRECI vegetation index became the most important variable in estimating carbon stocks compared to single-band channels. This is due to the use of red edge channels that have good sensitivity to vegetation and are highly correlated with mangrove canopies (Pham et al., 2020).

The vegetation index used to predict carbon values has an important role and is an important variable. This is done by research (Pham et al., 2020), obtaining results that vegetation indices can help predict forest surface carbon stocks. The vegetation index can reduce the effects of reflectance caused by external conditions of the field, such as shadows, to improve the relationship between carbon estimation values and vegetation indices (Taylor & Lu, 2007).

As for the single channel, it is not an important part of estimating carbon reserves because the wavelengths owned are not optimal in capturing reflection changes due to the influence of the chlorophyll content of the canopy (Frampton et al., 2013).

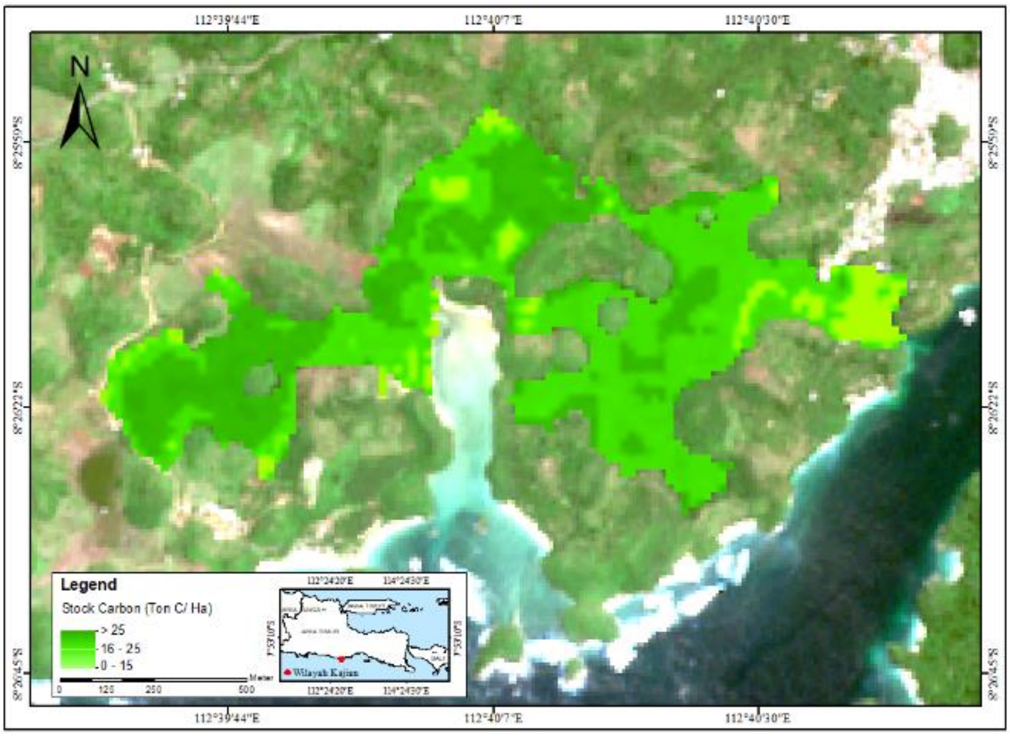

Figure 4 . Model Map AGC Sentinel-2

The results showed the estimation of carbon stocks using Sentinel-2 optical data, the most influential of which was the vegetation index. This is because Sentinel-2 imagery has the advantage of 3 red edge channels which are very effective in monitoring vegetation health through a canopy. Hence, it can potentially have a good correlation relationship with biomass. But in this study, the correlation value generated in predicting the carbon stock value of the image has a weak relationship even though the variable of the vegetation index can become the most important prediction variable.

AGC Model Evaluation

The performance of the spatial model of estimating the resulting carbon stock was assessed using RMSE. RMSE is used to determine errors from the resulting model and in conjunction with mean absolute error (MAE) to determine variations of model errors (Pham et al., 2020).

The resulting model error against the difference between the measured carbon data and the predicted one so that the best model will produce a high R^2 value. The results of predictions and tests of agc models generated from Sentinel-2 and Sentinel-1 images in this study can be seen in Table 2.

Table 2. AGC Model Evaluation

Prediction Data	AGC Model	
	Sentinel-1	Sentinel-2
R^2	0,11	0,22
RMSE	1,02	0,89
MAE	0,84	0,75
Test Data		
R^2	0,01	0,18
RMSE	1,45	1,25
MAE	1,20	1,08

Based on Table 2, the correlation value of R^2 from the results of prediction data using Sentinel-2 imagery produces values of 0.22 and Sentinel-1, which is 0.11. This value is better when compared to the test data results, namely 0.01 and 0.18. The R^2 value is still relatively small, so the matter has not been able to perfectly explain the relationship between the predicted data and the actual data.

Meanwhile, the results of this study's RMSE and MAE values from prediction data and test data are inversely proportional to the R^2 value. The predicted data value development is lower than the test data. According to (Pham et al., 2018), lower RMSE and MAE values show a better regression model, while the difference between small arms and mae values shows a smaller variation in error rates. The results of this study showed a lower error rate because the difference in values resulting from RMSE, and MAE was not too significant. This indicates that the carbon stock model produced with predictive data has obtained good results, although the correlation value of R^2 is still relatively small.

Accuracy Test

Accuracy tests are carried out to determine the level of accuracy and confidence of the model from the prediction results that have been produced. This study used test data of 12 data samples for accuracy tests. The random forest method obtains the test data through automatic data sharing. This study used the standard error of estimate (SE) method for the accuracy test and plot goodness of fit 1: 1. Calculations of the accuracy test with SE of the resulting carbon prediction model can be seen in Table 3.

Table 3. Carbon Model Accuracy Test

	Carbon Model	
	Sentinel-2	Sentinel-1
SUM	15,23	15,37
Count	12	12
SE (ton C/piksel)	1,23	1,24
Mean	1,29	1,29
Stdev	1,15	1,15
CL95%	0,60	0,60
Upper Range	1,90	1,90
Lower Range	0,68	0,68
Max Error	1,78	179,73
Min Error	64,96	65,26
Max Accuracy	35,03	34,73
Min Accuracy	-78,90	-79,73

Based on the results of the model accuracy test from Sentinel-2, it got an SE value of 1.23 tons C / pixel and Sentinel-1 1.24 tons C / pixel. The smaller the value, the better. On the contrary, if the greater the matter, it is not good. A low SE value can be attributed that the result of the created model is good with minor errors. The maximum value of accuracy is 35.03%. Accuracy values that are not too high can be relieved by the uneven distribution of samples to the density of vegetation in the field.

While the results of the accuracy test using the plot method of the goodness of fit 1: 1 can be seen in Figure 4.

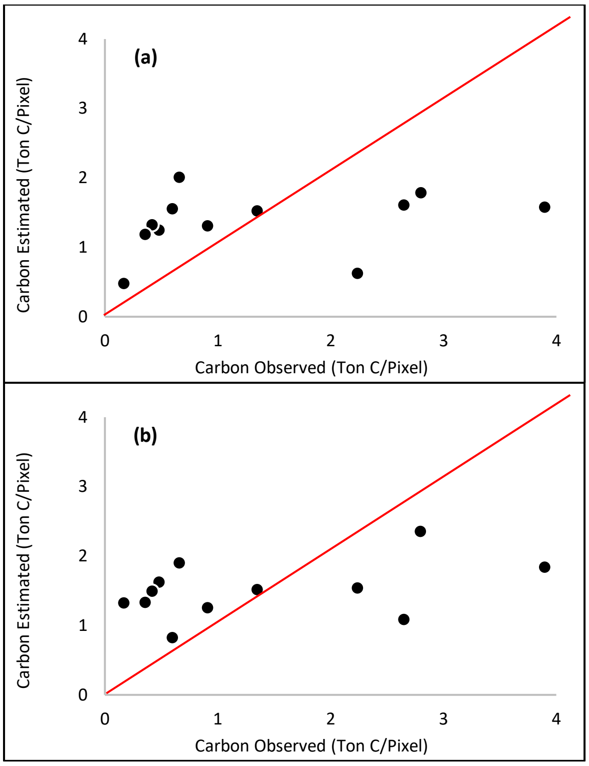

Figure 4. Graphic *plot goodness of fit* 1:1 (a) Sentinel-1 dan (b) Sentinel-2

The results of the accuracy test with the 1: 1 plot method showed the effects of predictions that the pattern tends to be overestimated. Field data measurements can influence the cause of overestimated results of this study in the form of mangrove vegetation DBH, which is limited to a minimum size of 15 cm in diameter, while spectral reflections from the image can detect vegetation with a smaller diameter due to the influence of the canopy density effect.

CONCLUSION

The calculation of mangrove carbon stocks is carried out without considering mangrove species. The results of carbon estimation with Sentinel-2 are 10-40 tons C / Ha and 2,025 tons C. While the estimation results using Sentinel-1 data get a result of 15-37.5 tons C / Ha and 2,126 tons C / Ha. The IRECI vegetation index is the most important prediction variable for mangrove carbon. Estimated carbon stocks with Sentinel-2 showed better results than Sentinel-1.

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