Predictive Model of Mangroves Carbon Stocks in Kedah, Malaysia using Remote Sensing

T M Z T Hashim¹,², M N Suratman¹,³, H R Singh¹,², J Jaafar³ and A N Bakar²,⁴

¹Faculty of Applied Sciences, Universiti Teknologi MARA (UiTM), 40450 Shah Alam, Malaysia.
²Centre for Biodiversity and Sustainable Development, 40450 Shah Alam, Malaysia.
³Faculty of Surveying Science and Geomatic Universiti Teknologi MARA (UiTM), 40450 Shah Alam, Malaysia.
⁴Faculty of Administrative Science and Policy Studies, Universiti Teknologi MARA (UiTM), 40450 Shah Alam, Selangor

Corresponding e-mail: tmzarawie@gmail.com, nazip@uitm.edu.my

Abstract. Mangroves are recognized as an ecosystem that grow and dominate the coastal areas of tropical and sub-tropical regions across the world. They not only provide ecological and socio-economic support, but also play a pivotal role in offsetting an excess of carbon from the atmosphere. Despite the crucial roles provided by mangroves, the ecosystem has degraded at an alarming rate mainly due to anthropogenic activities. Remote sensing technology provides a new dimensional perspective in monitoring and estimating tree biomass and carbon stocks. Therefore, this study aimed at (1) estimating the carbon stocks of mangroves in Kedah, Malaysia, (2) investigating the relationships between mangrove stand parameters with spectral reflectance recorded from Landsat 8 Operational Land Imager (OLI) data, and (3) developing predictive models for estimating the carbon stocks of mangroves by combining the ground and Landsat 8 (OLI) data. For the purpose of this study, a total of 81 mangrove stand data sets measuring at 100 m × 100 m were collected throughout Kedah, Malaysia. Within the stand, seven randomly selected plots were established and all individual mangroves parameter (diameter at breast height (DBH) and height) were measured. The 81 stands were split into two independent data sets for developing and validating the models (56 and 25 stands, respectively). Multiple regression technique with least square approach was used in the model development process. From several good candidate models, a model consists of four predictive variables (bands 3 and 6, Normalized Difference Vegetation Index (NDVI) and simple ratio seems to be predicting reasonably well based on its simplicity and practicality (p≤0.001, $R^2 = 0.56$). Validation of the model has resulted in Mallow’s prediction criterion (Cp) value of 4.28 and Root Mean Squared Error (RMSE) of 4.11 Mg/ha. The information from this study may provide useful input for future research and can be crucial tools for the government and stakeholders in future decision making for the sustainability of mangrove resources.

Key word: Modelling, Carbon Stocks, Mangroves, Remote Sensing, Landsat 8 (OLI)
1. Introduction
Mangroves are complex combination of salt tolerance plants, shrubs, palms and ferns that exist and grow in coastal zone areas throughout tropical and sub-tropical regions. The high adaptability properties that possess by these halophytic trees enable them to thrive in the harsh condition such as the intertidal zones [1-3]. Despite only exist in a restricted coastal area and account only 2.4% of world forests, they provides tremendous ecological function [4-6] and instrumental for social-economic support [7, 8]. Unfortunately mangroves have been degraded at an alarming rate due to the climate change factors and negative intervention from anthropogenic disturbance. With a constant loss rate of 1% annually due to over exploitation [9], mangroves are predicted to be extinct in the next 100 years [10].

The acceleration of global climate change in recent decades has generated interest among researchers to study the potential of mangroves to store carbon. Mangroves are reported to have the ability to store carbon four times larger than most other types of tropical forests around the world [11, 12]. The ability of the mangroves to absorb excess CO\(_2\) from the atmosphere and store in their part as biomass is 40% higher than the dry land forest ecosystem. Perhaps the least quantify but yet critically important ecosystem services provided by the mangroves are its ability to store excess carbon from the atmosphere. It is crucial to understand the role of the mangroves to sequester carbon as it gives more information in mitigating global climate change [13].

Remote sensing technology has provided a new frontier for effective management and planning when it comes to studying treacherous and remote areas such as the mangroves ecosystem [14]. Recently launched Landsat 8 Operation Land Imager (OLI) has opened a new dimension for studying forest biomass and carbon stocks with enhanced and improvement of sensors compare to its predecessor [15, 16].

Since mangroves have an important role in global carbon budget and mitigating climate change, accurate and reliable information is needed for estimating their carbon stocks. Therefore, this study aimed at (1) estimating the carbon stocks of mangroves in Kedah, Malaysia, (2) investigating the relationships between mangrove stand parameters with spectral reflectance recorded from Landsat 8 Operational Land Imager (OLI) data, and (3) developing predictive models for estimating the carbon stocks of mangroves by combining the ground and Landsat 8 (OLI) data. The information from this study may provide baseline information and useful tool for stake holders and mangroves related agencies in making resource forecasts, and assist in the development of management of mangrove forests.

2. Methods

2.1 Study Site and Sampling
This research was conducted within a 7,686.92 ha of mangrove forests located at Merbok Mangrove Reserve (MMR) in the coordinates of 5° 41’ 36” N and 100° 25’ 22” E and Langkawi Island (Sungai Kilim and Sungai Kisap) at coordinate 6° 23’ 37” N and 99° 51’ 90” E, in Kedah, Malaysia (Figure 1). The MMR can be found in the north-western of Peninsular Malaysia and near to Penang Island are considered as the fourth biggest mangroves area in Peninsular Malaysia after Perak, Johor and Selangor. The geographic terrain is flat in the study area with the elevation below 20 meters above the mean sea level. The mean monthly temperature is 26.1 °C and received mean monthly rainfall about 234.6 mm with high humidity all year round. The Merbok main streams directly flow to Strait of Malacca and connected by several small rivers along the line. The main stream stretched up to 35 km long to Sungai Petani town with seawater can inundate up to 30 km from seaward to landward area and the depth of the main river varying from 13-15 m.
Figure 1. Location of the study area.

A total of 81 mangroves stand with a size of 100M × 100M each was established in the study area. For each selected stand, sample plots of 25M × 25M were located using a stratified random sampling design with a random start. Seven sample plots were randomly established in each of the stands, and the mean for each forest stand parameter was calculated and used to represent the entire stands [17]. In all plots, diameters at breast height (DBH) were measured using DBH tape (1.3 m from the ground) and height using a hypsometer. For tree species that have prop roots such as the *Rhizophora spp.* the DBH was measured 30 cm above the highest prop root. A Global Positioning System (GPS) device was used to record the coordinate of each field plot. Data from 81 stands were further split into two independent groups. First, a set of 56 stands was used for building the models. Second, a set of 25 stands was used for validating the models. Tables 1 and 2 present a summary of the data set used for model building and model validation.

| Variable    | No. stands | Min.ᵃ | Max.ᵇ | Mean  | SDᶜ |
|-------------|------------|-------|-------|-------|-----|
| DBH (cm)    | 56         | 11.31 | 31.67 | 18.60 | 4.44 |
| Height (m)  | 56         | 9.06  | 22.32 | 14.06 | 2.21 |
| Band 2      | 56         | 0.08  | 0.10  | 0.09  | 0.01 |
| Band 3      | 56         | 0.06  | 0.08  | 0.07  | 0.01 |
| Band 4      | 56         | 0.04  | 0.05  | 0.04  | 0.01 |
| Band 5      | 56         | 0.21  | 0.43  | 0.30  | 0.04 |
| Band 6      | 56         | 0.04  | 0.11  | 0.71  | 0.01 |
| Band 7      | 56         | 0.01  | 0.04  | 0.02  | 0.01 |

Table 1. Summary of Data Set Used For Model Building.

| Variable    | No. stands | Min.ᵃ | Max.ᵇ | Mean  | SDᶜ |
|-------------|------------|-------|-------|-------|-----|
| DBH (cm)    | 25         | 7.30  | 27.88 | 17.21 | 3.88 |
| Height (m)  | 25         | 7.39  | 17.90 | 13.37 | 3.22 |
| Band 2      | 25         | 0.09  | 0.09  | 0.08  | 0.01 |
| Band 3      | 25         | 0.06  | 0.08  | 0.07  | 0.01 |
| Band 4      | 25         | 0.04  | 0.05  | 0.04  | 0.01 |
| Band 5      | 25         | 0.23  | 0.40  | 0.29  | 0.03 |
| Band 6      | 25         | 0.05  | 0.10  | 0.07  | 0.01 |
| Band 7      | 25         | 0.01  | 0.03  | 0.02  | 0.01 |

Table 2. Summary of Data Set Used For Model Validation.

Notes: a minimum, b maximum, c Standard deviation
2.2. Carbon Stocks Calculation

To calculate the amount of carbon stocks stored in mangroves, the calculation of Above Ground Biomass (AGB) was performed first using published allometric functions from previous research. Table 3 shows the allometric function used to calculate the estimation of mangrove AGB.

Table 3. Allometric function for AGB estimation.

| Species                  | Allometric Function | Source |
|--------------------------|--------------------|--------|
| Avicennia marina         | AGB=0.188D^{2.35}  | [18]   |
| Bruguiera gymnorrhiza    | AGB=0.186D^{2.31}  | [19]   |
| Bruguiera parviflora     | AGB=0.168D^{2.42}  | [19]   |
| Rhizophora apiculata     | AGB=0.235D^{2.42}  | [20]   |
| Xylocarpus granatum      | AGB=0.082D^{2.59}  | [19]   |
| General equation         | AGB=0.1848D^{2.46} | [21]   |

Notes: AGB = above ground biomass (kg), D = diameter at breast height (cm)

The value of obtained AGB that was derived from the allometric function was further multiplied by a specific carbon concentration that ranges between 0.46-0.50 [22].

2.3. Image acquisition and pre-processing

The image used was a full scene of Landsat 8 OLI, path 128 rows 56, recorded on 27 February 2014 with less than 10% cloud coverage that is obtained from the United States Geological Survey (USGS). Landsat 8 imagery has a spatial resolution of 30 m for band 1-7 and 9, while band 8 (panchromatic) has a resolution of 15 m [16]. The Landsat image closest to the date of ground data collection which was the year 2012 - 2014 with minimum cloud coverage was chosen. The image was geometrically corrected to the Malaysia Rectified Skew Orthomorphic (MRSO) projection system with root mean squared error (RMSE) of less than 0.5 pixels using ERDAS Imagine 9.1. In addition to radiometric calibration, atmospheric correction was performed to correct the Landsat digital numbers (DNs) to ground reflectance.

For the purpose of this study, topographic (series L 7030; scale 1:50,000 and series DNM 5101; scale 1:50,000) and land cover/use (2008, scale 1:50,000 and 2010, scale 1:200,000) map sheets of Kedah obtained from the Department of Survey and Mapping and Department of Agriculture, Malaysia, respectively, were used as reference maps. The boundaries for each of the field sampling stands were delineated on the imagery based on mangroves stand maps rectified to the imagery, and corresponding spectral measurement for each stand was extracted from the individual Landsat 8 bands for statistical analysis.

2.4. Carbon Stocks Modelling

The relationships between the stand variables and Landsat 8 data was done by calculating their Pearson’s correlation coefficient (r) and inspections of scatter plot diagram of response variables (carbon stocks, Y) against the single bands and vegetation indices (X). Table 4 presents the predictor variables used for the regression model fitted to carbon stocks. The selection of Landsat 8 individual band and the vegetation indices that were used for this study was based on extensive reviews of literature and the understanding of nature and sensitiveness of each selected bands with the vegetation [16, 23, 24]

Table 4. Variables Used for Regression Models Fitted to Carbon Stocks.

| No | Predictor Variables                  | Variable labels |
|----|--------------------------------------|-----------------|
| 1  | Individual Landsat 8 (OLI) bands     | B2, B3, B4, B5, B6 and B7 |
| 2  | Normalized Difference Vegetation Indices | NDVI            |
| 3  | Ratio Vegetation Indices             | RVI             |
| 4  | Soil-Adjusted Vegetation Indices     | SAVI            |
| 5  | Simple Ratio                         | SR              |

4
A normality test was performed on the data using Shapiro-Wilk test to find out whether the data normally distributed. The inspection of the normality test and scatter plots for carbon stock against single Landsat-8 bands and vegetation indices revealed the data set are not normally distributed and has non-linear relationships. Therefore, transformation methods were used to transform the dependent and independent variables. After the transformation process, it was found that the hyperbolic relations model more suited for the carbon stocks transformation compare to other transformations types of models. It can be represented as follow:

\[ Y = b_0 + b_1 \left( \frac{1}{x} \right) + b_2x \]

‘Good’ model candidates were selected based on analysis of the usefulness of variables in prediction, associated with automatic search methods in Statistical Package System Software (SPSS) 22.0, such as forward selection, backward elimination and stepwise regression.

During the building process, several model assumptions such as multicollinearity, variance inflation factor (VIF), tolerance coefficient, Durbin-Watson test and homescedasticity of each of the produced model was examined to ensure the models are valid and reliable. Statistics such as coefficient of determination (R\(^2\)), Adjusted R\(^2\), Standard Error of Estimates (SEE) and significant level (\(\alpha = 0.05\)) were used to determine the best model. Histogram of the residuals and P-P plots of cumulative frequency of predicted value against cumulative frequency of residuals and Shapiro-Wilk test was conducted. Plots of measured against predicted values and predictions errors of predicted variables against response variables values in the validation data sets (n=25) were observed to discover any areas that underestimated or overestimate.

Accuracy of the model was assessed by applying the models to the test data sets and calculating the root mean squared error (RMSE) of predicted value against actual value, estimated correlation index square (I\(^2\)) and Mallow Cp criterion.

### 3. Results and Discussion

#### 3.1. Estimation of Carbon Stocks

From the study, a total of 20,164 individual mangroves trees were recorded. In 81 mangroves stands across MMR and Langkawi, fifteen mangroves species were successfully identified in both of the study site these included: *Rhizophora apiculata*, *Rhizophora Mucronata*, *Bruguiera parviflora*, *Bruguiera cylindica*, *Bruguiera gymnorrhiza*, *Bruguiera sexangula*, *Ceriops tangal*, *Avicennia marina*, *Avicennia officinalis*, *Sonneratia alba*, *Sonneratia ovata*, *Sonneratia casilarii*, *Xylocarpus granatum*, *Xylocarpus moluccensis* and *Excoecaria agallocha*. However the most dominant species found in both study area was the *R. apiculata* species. This comes to an agreement to study conducted by [20], who stated that mangroves found in Asia Pacific largely dominated by *R. apiculata*. Another study conducted in Langkawi also reported that the most abundant mangroves species in the area belong to this species [25].

The calculations of carbon stocks for both of the study site were based on mangroves DBH only and did not include the tree height due to the concerns that it may introduce errors in the estimation. Even though height can be an important candidate in estimating the carbon stocks of mangroves, the structure of the mangroves itself that has a high density of trees and dense canopy layer makes it difficult to measure during sampling and may cause error [26, 27]. The mean of carbon stocks in both study area was 67.29 Mg/ha. The lowest estimation was 16.88 Mg/ha while the highest was 138.20 Mg/ha. Results from this study showed a similar pattern to the previous study that was conducted in Langkawi, where the estimation of carbon stocks ranged between 10 Mg/ha to 161 Mg/ha [25]. Another study that was done in Southern Thailand found that carbon stocks in riverine mangrove forests were between 12.40 Mg/ha to 449 Mg/ha [28].
3.2. Relationship between Carbon Stocks with Spectral Reflectance

Table 5 presents the correlation matrix of carbon stocks with Landsat-8 individual bands (bands 2 – 7). From the table, there is a positive correlation between the carbon stocks and each of the Landsat 8 bands.

| Variables          | C. Stocks (Mg/ha) | B2   | B3   | B4   | B5   | B6   | B7   |
|--------------------|------------------|------|------|------|------|------|------|
| C. Stocks (Mg/ha)  | 1.00             |      |      |      |      |      |      |
| B2                | 0.50**           | 1.00 |      |      |      |      |      |
| B3                | 0.52**           | 0.79** | 1.00 |      |      |      |      |
| B4                | 0.35**           | 0.68** | 0.83** | 1.00 |      |      |      |
| B5                | 0.33*            | 0.55** | 0.67** | 0.31** | 1.00 |      |      |
| B6                | 0.44**           | 0.57** | 0.87** | 0.79** | 0.57** | 1.00 |      |
| B7                | 0.20             | 0.49** | 0.70** | 0.75** | 0.52** | 0.84** | 1.00 |

From the correlation analysis, Landsat 8 bands 2 and 3 show a moderate significant correlation with carbon stocks as compared to other bands with both r values of 0.52 (p=0.0001) and 0.50 (p=0.0001) respectively. Bands 4 and 6 also shown significant correlations with carbon stocks with both r values 0.44 (p=0.001) and 0.33 (p=0.008). However, for band 7, there is a weak positive correlation between Landsat-8 individual bands with carbon stock.

The correlations between the carbon stocks and Landsat individual bands have been discussed in many previous literatures. A study that was performed in three countries Malaysia, Thailand and Brazil using Landsat Thematic Mapper (TM) in an effort to quantify the tropical forest biomass and carbon stocks found that r value for AGB and carbon stocks versus Landsat TM individual bands ranges between -0.48 to 0.50 [29]. Meanwhile study that focused on mangrove AGB and carbon stocks in China using various multispectral sensor report that there were weak but significant correlation between AGB and carbon stocks with band 3 (0.43), band 4 (0.39) [30].

3.3. Carbon stocks modelling

After transformation procedure, the data was checked and found out that the data followed and normally distributed with a p-value greater than 0.05. Carbon stocks estimation models were produced using a stepwise and backward elimination procedure from multiple regression analysis methods. During the development of models, five best models were chosen from the analysis and other model was excluded from this study due to the complexity of the model and comprises too many variables. For the carbon stock, the predictive model analysis of practicality and predictive ability (R², adjusted R², I², RMSE, and Mallow Cp) for each of the models were strongly considered where the selection of the model was based on the usefulness and importance to the objective of study. Table 6 shows five final regression models developed for carbon stocks and they were all statistically significant (p<0.05).

From Table 6, all the final candidate regression models were highly significantly (p<0.000) where the range of R² value is 0.56-0.50. Therefore it can be concluded that all the carbon stocks models were moderately good representations on how predictor variables that were chosen for this study contributed to estimating the carbon stocks of the mangroves. Models 3 and 4 were found to have the highest R² with both of the model consist of four predictor variables (R²=0.56, p=4), followed by model 5 (R²=0.55, p=4) and lastly models 1 and model 2 (R²=0.50, p=3). The highest adjusted R² was observed in models 3 and 4 (0.53) and the lowest adjusted R² was recorded for models 1 and 2 (0.47). SEE values ranged from 19.42 Mg/ha to 20.61 Mg/ha. Results of validation analysis for estimating carbon stocks are shown in Table 7.

For better estimation of carbon stocks, the predictive models were selected based on the highest I² and Cp value closers to the number of a predictor variable included in the models. For this study, the I² was observed to have the value that almost close to each other. For the predictive carbon stocks model, the I² ranged between 0.42-0.46 where the highest I² is in model 3 and the lowest I² was observed in
models 2 and 4. Although $I^2$ is an important criterion to determine the best predictive model, Cp value also needs to be considered, where the analysis suggests the acceptable number of a predictor that should exist in the predictive models. From Table 7, the Cp values were observed between 3.37-7.14 for each of the predictor models. Meanwhile, RMSE is a good measure of how accurately the model predicts the response and the lower RMSE value indicate a better fit of the model.

Based on Table 7 the range of RMSE was 20.90 Mg/ha to 22.38 Mg/ha. Even though both of models 1 and 5 produced among the highest analysis of $I^2$ (0.44), the number of predictors that present in the model are different from Mallows’ Cp analysis where for the model 1 (p=3, Cp=7.14) and model 5 (p=4, Cp=3.37). Models 2 and 4 have the lowest $I^2$ as compared to other model (0.42) and the analysis of Mallows’ Cp also indicate a different number of predictor in the analysis compare to what produced by both candidate model, where for model 2 (p=3, Cp=4.37) and model 4 (p=4, Cp=3.48). The highest $I^2$ was recorded in model 3 with the Mallows’ Cp analysis value shows a similar value in the number of predictors (p=4, Cp=4.28). The highest RMSE was recorded for model 2 (22.38 Mg/ha) while the lowest was recorded for model 1 (20.90 Mg/ha).

### Table 6. Regression Models for Carbon stocks (n=56 stands).

| Model No | Predictor Variables                                                                 | p  | $R^2$ | Adj. $R^2$ | SEE (Mg/ha) |
|----------|-------------------------------------------------------------------------------------|----|-------|------------|-------------|
| 1        | $C = (\log_{10} B3), (\log_{10} B6), (\log_{10} Ratio 1)$                          | 3  | 0.50  | 0.47       | 20.61       |
| 2        | $C = (EXP - B3), (EXP - Ratio 1), (EXP - B6)$                                       | 3  | 0.50  | 0.47       | 20.53       |
| 3        | $C = \left(\frac{1}{B3}\right) \cdot \left(\frac{1}{NDVI}\right) \cdot \left(\frac{1}{Ratio 1}\right)$ | 4  | 0.56  | 0.53       | 19.57       |
| 4        | $C = \left(\frac{1}{B3}\right) \cdot \left(\frac{1}{RVI}\right) \cdot \left(\frac{1}{Ratio 1}\right)$ | 4  | 0.56  | 0.53       | 19.42       |
| 5        | $C = (\log_{10} B3), (\log_{10} B6), (\log_{10} Ratio 1), (\log_{10} Ratio 2)$      | 4  | 0.55  | 0.52       | 19.68       |

Notes: p is number of predictor variables in the model, $R^2$ is Coefficient of determination, Adj. $R^2$ is adjusted $R^2$, SEE is standard error of estimate, B3 is Landsat 8 band 3, B6 is Landsat 8 band 6, NDVI is Normalized Difference Vegetation Index, RVI is Ratio Vegetation Index, Ratio 1 is Landsat 8 band 6 versus band 4, Ratio 2 is Landsat 8 band 6 versus band 5.

### Table 7. Summary of Regression Model Validation for carbon stocks (n=25 stands).

| Model no | p  | $I^2$ | Cp  | RMSE (Mg/ha) |
|----------|----|-------|-----|--------------|
| 1        | 3  | 0.44  | 7.14| 20.90        |
| 2        | 3  | 0.42  | 4.37| 22.38        |
| 3        | 4  | 0.46  | 4.28| 22.24        |
| 4        | 4  | 0.42  | 3.48| 21.94        |
| 5        | 4  | 0.44  | 3.37| 21.30        |

[31] in the study to determine the carbon stocks of Karimunjawa Island, Indonesia found out that the $R^2$ was 0.32 using integration between ground survey data and Landsat 7 ETM+. Findings from this study show NDVI and simple ratio index were among selected predictors that performed well for the estimation of carbon stocks of the mangroves. The study also indicated that the low value of $R^2$ produced by the research are resulted from the complexity of the mangroves community, spatial displacement of GPS reading and error in the correction done to the Landsat 7 ETM+ image during the image pre-processing. However [32] produces a promising result of $R^2$=0.72 during the study to quantify mangroves carbon stocks in Matang mangrove, Malaysia using Landsat TM and SPOT-5 imagery data. The study concluded that the mangroves stand structure that was dominated by homogeneity stand (Rhizophoraceae) enables the possibility of using the optical remote sensing to estimate the mangroves carbon stocks. Study in estimating the carbon stocks of mangroves species A. marina stand in Thane Creek, India using a combination of ground data and Resourcesat-2 LISS4 Standard Multispectral Image produce a successful result of $R^2$=0.96 [33].

Based on the statistical analysis of the best predictive ability and practicality of the final models, model 3 was chosen as the best fit model for carbon stocks estimation using the following:
Where C is carbon stocks (Mg/ha), B3 is Landsat 8 band 3, Ratio 2 is simple ratio index, NDVI is Normalized Difference Vegetation indices and B6 is Landsat 8 band 6.

4. Conclusion
From this study, the total carbon stocks for mangroves in Kedah were estimated to range from 16.88 Mg/ha to 138.20 Mg/ha with an overall mean of 67.29 Mg/ha. The relationship between the carbon stocks and satellite spectral reflectance indicated that there is a positive correlation between carbon stocks with Landsat-8 individual bands (bands 2 – 7). Bands 3 and 2 show a significant moderate correlation with carbon stocks compared to other bands with both r values of 0.52 (p=0.0001) and 0.50 (p=0.0001) respectively. There are four best predictor variables to estimate the carbon stocks of mangroves which include Landsat 8 band 3, band 6, NDVI and simple ratio that are correlated to carbon stocks ($R^2 = 0.56$, RMSE = 22.24 Mg/ha). Although the predicted model produces moderately good relationships for carbon stocks study, it can still be concluded that Landsat data have the potential for estimating carbon stocks in Malaysia. Information from this study may provide useful tools for stakeholders and government agencies in making resources forecast and planning on carbon stocks and can be a baseline data to understanding the role of mangroves in combating the global climate change.

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