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ESTIMATION OF ABOVEGROUND BIOMASS IN MANGROVE FORESTS USING VEGETATION INDICES FROM SPOT-5 IMAGE

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Mangrove forests play a pivotal role in climate change mitigation through biomass and carbon storage. Due to rising concern towards global climate change and carbon sequestration, a practical method to estimate the forest biomass and carbon stocks is necessary. Therefore, this study attempted to quantify aboveground biomass (AGB) within the mangrove ecosystem in Malaysia. A total of 150 sample plots at Matang Mangrove Forest Reserve were established in 2014. This study estimated and mapped the AGB based on Systeme Probatoire d'Observation de la Terre 5 (SPOT-5) satellite image. Four types of vegetation index were examined in this study. Simple and multilinear regression methods were employed which correlated field data with the derived vegetation indices for the estimation of AGB in the entire study area. Results demonstrated that the multilinear regression method improved the accuracy of estimation. Estimated AGB ranged between 33.65 and 437.46 Mg ha^{-1} with an average of 133.97 Mg ha^{-1}. Total AGB for the entire study area was approximately 1.30 million Mg. Error of estimation largely occurred when AGB exceeded 300 Mg ha^{-1}. The study showed that multilinear technique was reliable for the estimation of AGB in mangrove forests based on the SPOT-5 image.

Keywords: SPOT-5 image, quantification, carbon stock, managed mangroves, ecosystem

INTRODUCTION

Mangrove forests protect the coastal land against destruction of tsunamis and storms. Mangrove forests also provide habitat for various aquatic life forms and function as filter, which improves the quality of water. Total area of mangrove forest was approximately 2% (645,852 ha) of the total land area in Malaysia in 1994 (Azahar & Shah 2003). However, the area of mangrove forest in Malaysia has been gradually diminishing, and in 2014, has reduced to approximately 580,000 ha (Roslan & Shah 2014).

Mangrove forests thrive near coastal areas, which function as carbon pools (Patil et al. 2014). The soil of mangrove forest stores significant amount of carbon compared with other types of forest given its high sediment concentration (Tateda et al. 2005, Patil et al. 2014). Average carbon storage in mangrove soil is five times larger than in other types of forest soil (Kauffman & Donato 2012). Thus, it is crucial to study the biomass of mangrove trees in order to describe the changes of climate patterns at the regional and global scales.

Application of remote sensing is also crucial to obtain pertinent information of landuse cover and landuse change over extensive coverage areas. There are several methods to estimate stand biomass using remote sensing data. Normalised difference vegetation index (NDVI) is one of the vegetation indices which assess and monitor photosynthetically active biomass of plant canopies (Tucker 1979, Gitelson et al. 1996, Sweet et al. 2015). The NDVI utilises two wavelength channels from the optical satellite images, namely, red infrared and near infrared (NIR) to distinguish vegetation from other types of land cover. It is particularly useful for vegetation studies because the leaf surface, canopy cover and chlorophyll concentration are significantly sensitive towards the wavelength channels of red and NIR (Tucker 1979, Saliola 2014).

The combination of field-measured and remote sensing data assesses aboveground biomass (AGB), carbon stock and their changes over extensive coverage areas (Kiyono et al. 2011). Similarly, the combination of aerial photography and lower resolution satellite images such as Landsat and Systeme Probatoire d'Observation de la Terre 5 (SPOT-5) are also essential in the assessment and mapping of mangrove forests (Heumann 2011). However, higher resolution image is preferred when it comes to mapping and monitoring over small coverage area. Nonetheless, the utilisation of remotely-sensed data alone could be rather limited without the procurement of field data.

Therefore, this study investigated the usefulness of combining vegetation indices derived from SPOT-5 images and field sampling data in assessing AGB and carbon stocks of the Matang Mangrove Forest Reserve (MMFR), Perak. The improvement in the relationship between field sampling and satellite imagery using multilinear regression method is also discussed in this paper.

MATERIALS AND METHODS

Study area

The study was conducted at Kuala Sepetang (South) Forest Reserve, which is part of the MMFR (Figure 1). The total area of MMFR is about 41,000 ha. However, this study only considered 9884 ha of the MMFR. The forest was gazetted as a permanent forest reserve in 1906 and it is managed mainly for charcoal production. Located at the north-west coast of Peninsular Malaysia, MMFR is under intensive scientific management and considered as the best managed mangrove forest in the world (Okamura et al. 2010).

The main tree species found in MMFR are *Rhizophora apiculata* (locally known as bakau minyak), *Rhizophora mucronata* (bakau kurap) and *Bruguiera parviflora* (lenggadai) (Hamdan et al. 2014). Small channels usually bring in high quantities of *B. parviflora* propagules. Being an opportunist, this species rapidly takes root in clear-felled areas, which impairs the growth of *Rhizophora* species. Another *Bruguiera* species that mainly moves seawards is *B. cylindrical* (berus) but is considered inferior to *Rhizophora* species as raw material for charcoal production. Therefore, extensive areas having this species remain unexploited. Based on the ecological settings, the MMFR is classified into four main species, which are (1) *Avicennia-Sonneratia,* (2) *Rhizophora,* (3) *B. cylindrica* and (4) *B. parviflora* (Roslan & Shah 2014).

Satellite data

This study utilised the SPOT-5 satellite images, which were acquired on 13 December 2014. These images were supplied by the Malaysian Remote Sensing Agency. These images comprised four multispectral bands and one panchromatic band, which had spatial resolution of 10 and 5 m respectively. The four bands in multispectral were green (band 1, wavelength 0.51–0.59 μm), red (band 2, 0.61–0.68 μm), NIR (band 3, 0.78–0.89 μm) and short-wave infrared (band 4, 1.58–1.75 μm).

Field data

Field survey for the sample plots was conducted between October 2014 and March 2015. The location of the sample plots was restricted to easily accessible areas based on simple random sampling. Tree parameters such as diameter at breast height (DBH) and height were recorded individually. All trees with DBH $\geq$ 1 cm in the sample plot were measured using diameter tape at 30 cm above the highest prop roots. The coordinates for each plot and year of felling operation were also recorded. Unidentified leaf samples in the field survey were identified in the herbarium. Tree inventory and sampling were conducted in a sample plot of 0.1 ha. Radius of the circular plot was 17.84 m (Figure 2). The coordinate centre of the plot was determined using Garmin GPS device. This study established 150 sample plots and the total area of inventoried plots was 15 ha.

Estimation of plot-based AGB

Species-specific allometric equations were applied to estimate the total AGB (Komiyama et al. 2005). Using the Global Wood Density Database (Chave et al. 2009, Zanne et al. 2009) density values of oven-dry wood for all species in the mangrove forest is provided in Table 1. Study by Mohd Hasmadi et al. (2015) was also used as reference. All tree species were identified so that the species-specific wood density can be applied for accurate AGB estimation.

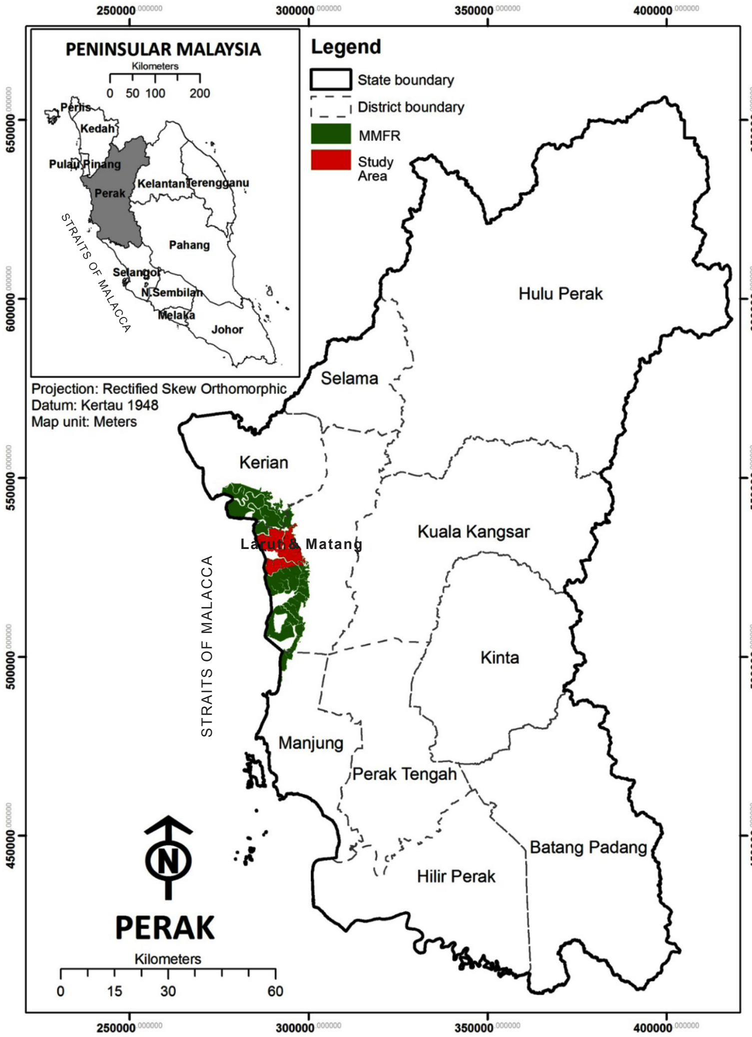

Figure 1 Location of the study area in Matang Mangrove Forest Reserve (MMFR), Perak

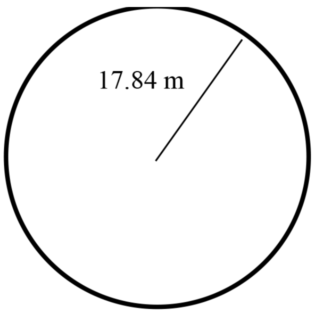

Figure 2 Layout design of the sampling plot

The estimation of AGB was based on DBH and wood density which were measured at the field. The equation for AGB can be expressed as follows:

$$AGB = 0.251\rho \times D^{2.46} \quad (1)$$

where AGB = aboveground biomass (kg), ρ = wood density (g cm^{-3}) and D = DBH (cm).

Pre-processing of image

The pre-processing phase, namely geo-referencing, atmospheric correction, radiometric correction, map enhancement, band combination and spatial filtering, was performed on the SPOT-5 images. The images were then geometrically registered to the Kertau RSO Malaya projection system. The reregistered

Table 1 Wood density for each species in mangrove forest according to the Global Wood Density Database

Species	Wood density ($g\ cm^{-3}$)
Rhizophora apiculata	0.843
Rhizophora mucronata	0.814
Bruguiera parviflora	0.772
Bruguiera gymnorrhiza	0.764
Avicennia alba	0.587
Sonneratia alba	0.509
Xylocarpus granatum	0.851
Sonneratia ovata	0.370
Ceriops tagal	0.837

Sources: Chave et al. (2009), Zanne et al. (2009)

images were subsequently pan-sharpened to obtain a higher resolution (Zhang & Mishra 2012). Pan-sharpening was performed by merging panchromatic image multispectral images to create a single high-resolution colour images, producing multispectral images with higher resolution pixels. The pixel resolution was improved from 10 to 5 m. Effects of atmospheric and radiometric were removed from the image to produce surface reflectance values for an improved image. This process involved the conversion of digital number values of SPOT-5 images into reflectance values.

Digital image processing

This study correlated certain variables from vegetation indices derived from SPOT-5 image with the measured AGB. These vegetation indices were (1) NDVI, (2) soil-adjusted vegetation index (SAVI), (3) green NDVI (GNDVI), and (4) global environment monitoring index–NDVI (GEMI–NDVI). The equations for these vegetation indices are provided in Table 2. All image indices were used for regression analysis.

Statistical analysis

Prior to the model development, correlations between vegetation indices and AGB were developed using simple Pearson correlation coefficient (r) and multilinear regression model. The following simple linear regression was used:

$$Y = \beta_0 + \beta_1 X \quad (2)$$

Table 2 Equations for selected vegetation indices

Equation for vegetation index	Source
$NDVI = \frac{P_{IR} - P_R}{P_{IR} + P_R}$	Rouse et al. (1974)
$SAVI = (1 + L)\ \frac{(P_{IR} - P_R)}{(P_{IR} + P_R + L)}$	Huete (1988)
$GNDVI = \frac{P_{NIR} - P_{green}}{P_{NIR} - P_{green}}$	Gitelson et al. (1996)
$GEMI\text{–}NDVI = n(1 - 0.25n)\frac{(P_R - 0.125)}{(1 - P_R)}$	Pinty and Verstraete (1992)

NDVI = normalised difference vegetation indices, SAVI = soil-adjusted vegetation indices, GNDVI = green NDVI, GEMI–NDVI = global environment monitoring index–NDVI; P = reflectance; wavelength channels: green, red (R), infrared (IR) and near infrared (NIR)

where β_0 = intercept, β_1 = value of slope line and X = value of independent variable. About two thirds of the dataset (100 plots) were selected for model development while one third (50 plots), for model validation. Coefficient of correlation (r^2) between the predictor and the measured AGB determines the strength of the regression model to represent two variables (Lawrence & Ripple 1998). An r^2 value of 1.0 signifies perfect fit of the data with the model.

A the multilinear regression, which was a combination between two or more independent variables, was applied in this study. Such combination typically provides high r^2 value, as reaffirmed by majority of previous studies (Hamdan et al. 2014a). Therefore, this technique has been adopted in this study to obtain improved r^2 values for the estimates. A multilinear regression model generally can be as expressed as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_{1-n} X_{1-n} + e \quad (3)$$

where β_0 = intercept, β_{1-n} = value of slope line for variable 1 – n and X_{1-n} = value of independent variable 1 – n.

Model validation and accuracy assessment

For model validation, the remaining 50 plots were used to measure the predictive accuracy of the estimation models. The error between predicted and measured AGB was calculated using vertical RMSE, as shown in the following equation:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_i - \hat{Y}_i)^2} \quad (4)$$

where N = number of check plots, Y_i = measured AGB at check plot i and i = derived/predicted AGB at position i.

Estimation of AGB and C stock in study area

The estimated AGB map was produced based on the best prediction function derived from the regressions. Each relationship between the two variables produced different values of r^2. The function that had the highest value of r^2 was used to estimate AGB in the entire study area.

RESULTS AND DISCUSSION

Summary of sample plots and estimated AGB

The DBH and height of tree samples for each species and AGB estimated from 150 plots are summarised in Table 3. All plots recorded a total of 15,142 trees where *R. apiculata* was dominant with 13,756 trees. DBH of the trees within all sample plots ranged between 1.5 and 42.5 cm. AGB varied between 24.35 and 462.40 Mg ha^{-1}. The total AGB estimated was 25,339.80 Mg ha^{-1}. The variation of the AGB in 150 plots is presented in Figure 3.

Table 4 summarises the results of total number of trees and total AGB, which were recorded and classified per diameter class. The mean height and DBH were calculated according to diameter class as well. Based on data from all sample plots, total AGB for the DBH class of 10–19 cm constituted more than 1258.55 Mg ha^{-1}. This DBH class recorded the highest number of trees (8235). DBH class 40–49 cm recorded the lowest number of trees (2) and total AGB value (3.43 Mg ha^{-1}).

Development of AGB prediction models

Conventionally, vegetation indices are utilised as predictors because of the relationship between spectral information catered by optical remote sensing data and vegetation biomass (Roy et al. 2010). The derived NDVI, SAVI, GNDVI, and GEMI–NDVI are illustrated in Figure 4. The scatterplots that have been generated from the linear regression analysis as shown in Figure 5, indicated the relationship between vegetation indices and measured AGB. The results demonstrated that NDVI attained the highest r^2 value (0.60) followed by GEMI–NDVI

Table 3 Average DBH and height for each species and AGB estimated from 150 plots

Species	Average of DBH (cm)	Average of height (m)	DBH (cm)		Height (m)		Count (Total: 15,142)
			Min	Max	Min	Max	
R. apiculata	13.70	11.26	1.50	42.50	2.50	19.00	13,756
R. mucronata	15.80	12.24	5.50	33.60	6.00	18.00	335
B. parviflora	11.40	9.71	5.20	33.60	4.00	18.00	873
B. gymnorrhiza	13.60	11.13	5.90	39.80	5.00	20.00	135
A. alba	14.24	11.56	7.50	40.00	6.00	19.00	18
S. alba	11.20	10.60	8.90	16.40	8.00	14.00	5
X. granatum	19.56	13.05	14.40	25.00	11.00	15.00	11
S. ovata	16.33	11.25	8.00	23.10	9.00	14.00	8
C. tagal	8.80	9.00	8.80	-	9.00	-	1

Estimation of total AGB from 150 sample plots

Sample plot	Minimum (Mg ha^{-1})	Maximum (Mg ha^{-1})	Average (Mg ha^{-1})	Total (Mg ha^{-1})
150	24.35	462.40	168.93	25339.80

DBH = diameter at breast height, AGB = aboveground biomass

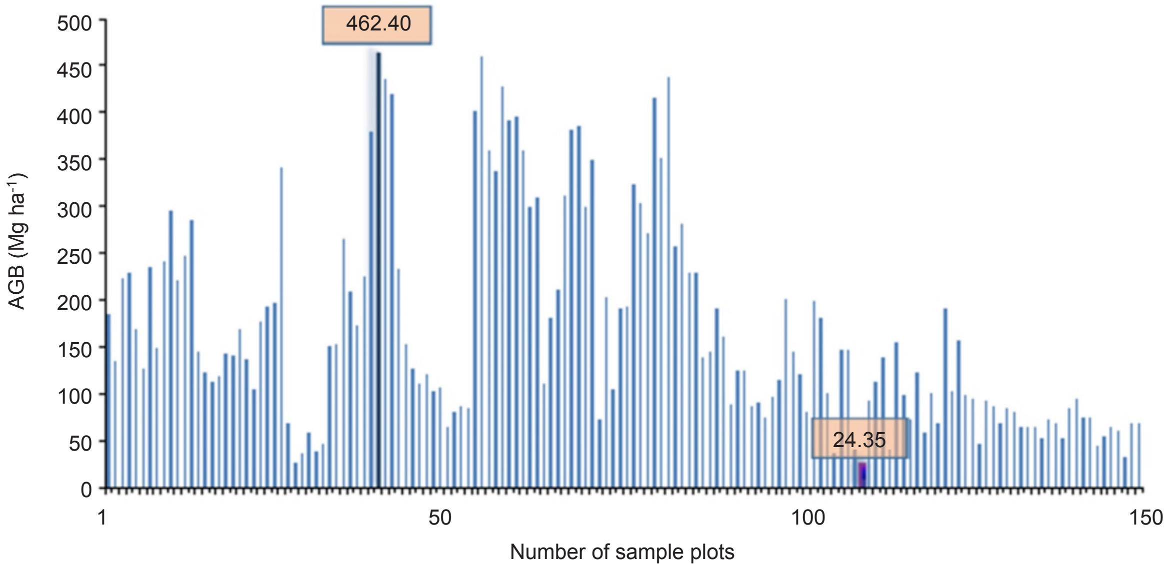

Figure 3 Variation of aboveground biomass (AGB) of all sample plots

Table 4 Summary of measurements according to diameter class

DBH class (cm)	1–9	10–19	20–29	30–39	40–49
Number of trees	4656	8235	2175	74	2
Total AGB (Mg^{-1})	180.00	1258.55	999.79	86.79	3.43
Mean height (m)	15.03	18.07	22.07	22.92	32.00
Mean DBH (m)	8.19	14.12	22.60	33.21	41.25

DBH = diameter at breast height, AGB = aboveground biomass

(0.51) (Table 5). There were no significant relationship between AGB and SAVI or GNDVI with the r^2 values obtained < 0.10. Therefore, NDVI and GEMI–NDVI were selected and combined as a single independent variable using multilinear regression to produce estimates of AGB for the entire study area.

Multilinear regression analysis

The measured AGB (between 92.12 and 307.78 Mg ha^{-1}) was utilised to validate the regression model. Figure 6 shows the perfect agreement between the measured and predicted AGB from the multilinear analysis. Table 6 summarises the prediction function that has been derived from the combination of NDVI and GEMI–NDVI. It is notable that the combination has slightly increased the r^2 value, and reduced the RMSE compared with the estimation models produced from single vegetation index. This implied that the combination of several independent variables was able to increase the accuracy of AGB estimates.

In order to further reduce the RMSE, AGB was divided into three intervals, namely, < 150, 150–300 and > 300 Mg ha^{-1} (Table 7). With that, the values of RMSE could be determined according to the AGB interval. RMSE was lowest (± 43.58 Mg ha^{-1}) when AGB ranged between 150 and 300 Mg ha^{-1} and as AGB exceeded 300 Mg ha^{-1}, RMSE increased (± 167.83 Mg ha^{-1}). RMSE was low when AGB ranged between 150 and 300 Mg ha^{-1} due to the high number of plots (Hamdan et al. 2015). Nonetheless, overall RMSE was ± 107.26 Mg ha^{-1} when all validation plots were integrated. Study by Goh et al. (2014) found that when ALOS PALSAR and SPOT-5 images were combined for estimation of AGB, the RMSE values were between 150 and 152 Mg ha^{-1} respectively. Thus, the overall RMSE obtained in this

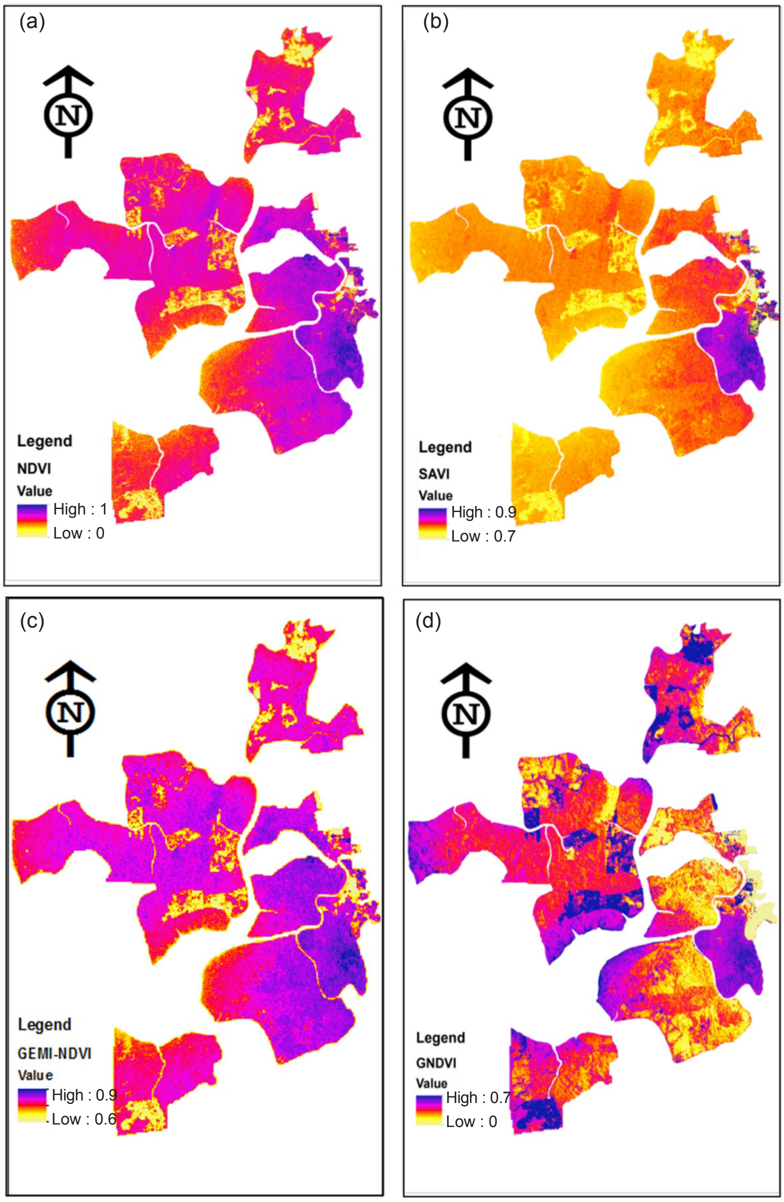

Figure 4 Images of four vegetation indices for the selected study area; NDVI = normalised difference vegetation indices, SAVI = soil-adjusted vegetation indices, GEMI–NDVI = global environment monitoring index–NDVI and GNDVI = green NDVI

present study was acceptable. Using NDVI and SAVI and the similar model, Hamdan et al. (2014a) obtained RMSE = 43.77 Mg ha^{-1} (r^2 = 0.59) and 68.21 Mg ha^{-1} (r^2 = 0.01) respectively.

Aboveground biomass distribution

The model developed from the multilinear regression analysis provided the highest rate of accuracy. The combination of estimated NDVI and GEMI–NDVI was applied to the selected site in MMFR with a total area of approximately 9884 ha. The minimum and maximum values of the AGB were 33.65 and 437.46 Mg ha^{-1} respectively. The overall AGB recorded approximately 1.3 million Mg ha^{-1}. Subsequently, for the entire MMFR, with a total area of approximately 41,000 ha, the overall AGB was 5.3 million Mg.

CONCLUSIONS

The linear regression is a commonly used method to estimate AGB in most studies. Since the study has derived four vegetation indices, the multilinear correlation, which can combine more than two variables in a single prediction model, was chosen for the AGB prediction in

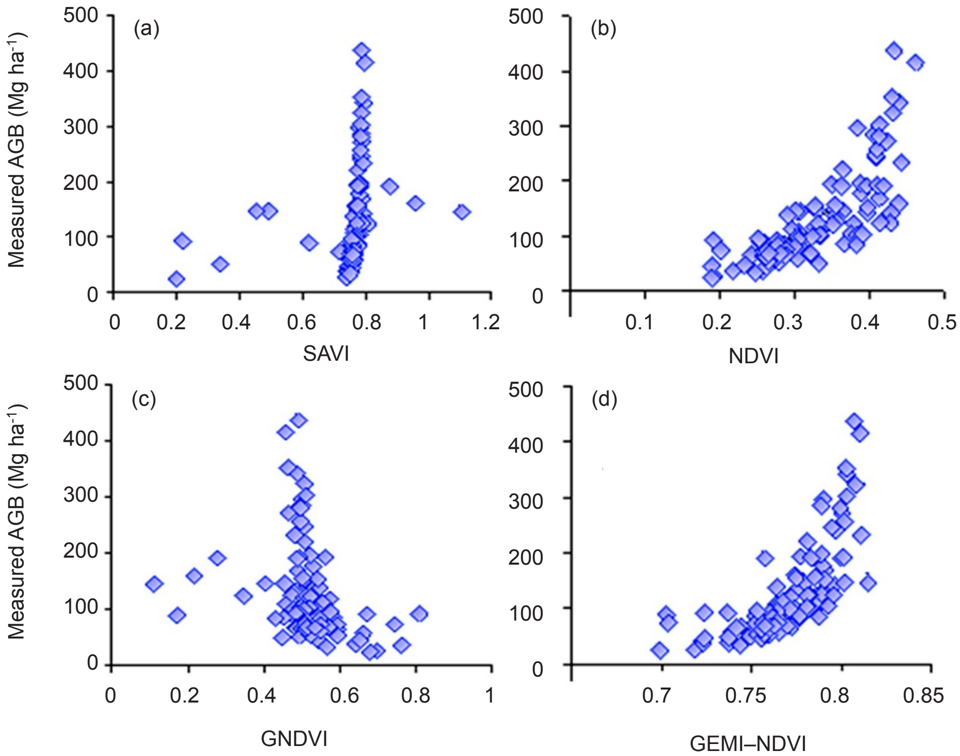

Figure 5 Satterplots of correlations between aboveground biomass (AGB) and vegetation indices: (a) SAVI = soil-adjusted vegetation indices, (b) NDVI = normalised difference vegetation indices, (c) GNDVI = green NDVI and (d) GEMI–NDVI = global environment monitoring index–NDVI

Table 5 Summary of simple linear regression models using single independent variable

Vegetation index	Model	r	r^2	Adjusted r^2	Residual error (± Mg ha^{-1})
NDVI	y = 973.87x – 190.62	0.78	0.60	0.60	54.62
GEMI–NDVI	y =2491.00x – 1789.50	0.71	0.51	0.51	60.47
SAVI	y = 183.31x – 7.51	0.23	0.05	0.04	84.02
GNDVI	y = -266.83x + 268.11	0.30	0.09	0.08	82.43

SAVI = soil-adjusted vegetation indices, (b) NDVI = normalised difference vegetation indices, (c) GNDVI = green NDVI and (d) GEMI–NDVI = global environment monitoring index–NDVI

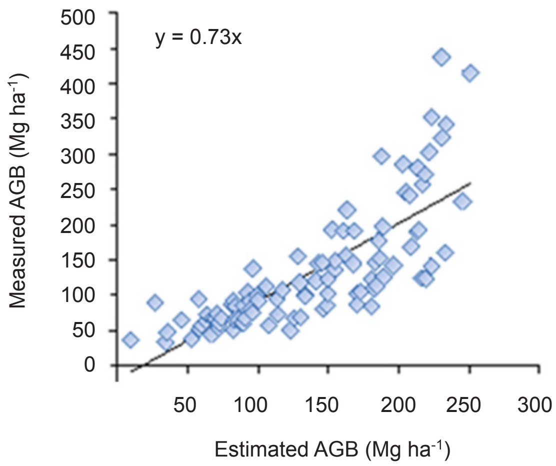

Figure 6 Scatterplot showing perfect agreement between measured and estimated aboveground biomass (AGB)

Table 6 Summary of simple linear regression using multiple independent variables

Vegetation index	Model	r	r^2	Adjusted r^2	Residual error (± Mg ha^{-1})
NDVI, GEMI–NDVI	y = 793.676(NDVI) + 574.770(GEMI–NDVI) – 574.219	0.80	0.61	0.59	54.45

Table 7 Values of root mean square error (RMSE) for multilinear variable according to ABG interval

Number of plots	AGB interval (Mg ha^{-1})	RMSE (± Mg ha^{-1})	Total RMSE (± Mg ha^{-1})
12	<150	68.63	107.26
21	150 – 300	43.58	
17	>300	167.83	

AGB = aboveground biomass

the entire study area. The developed model in this study provided the best estimation with r^2 value of 0.61. The range of the AGB estimated was between 33.65 and 437.46 Mg ha^{-1} with an average of 133.97 Mg ha^{-1}. The RMSE for the estimates was ±107.26 Mg ha^{-1}. A spatially distributed map of AGB within the study area has been produced and from the distribution, it was estimated that total AGB in Kuala Sepetang (South) that has an extent of 9884 ha was about 2,384,000 Mg.

The model was validated using independent validation plots and the predicted AGB was within agreement with the measured AGB, which was accurate at about 73%. Although there were some limitations produced by the study, the results were valid for the specific mangrove forest in the study area. Conclusively, the model developed by this study can be duplicated for estimations of AGB in similar mangrove ecosystem in Malaysia. The understanding on the forest biomass and carbon issues is one of the matters in efficient management practices.

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