ESTIMATING MANGROVE ABOVE-GROUND BIOMASS (AGB) IN SABAH, MALAYSIA USING FIELD MEASUREMENTS, SHUTTLE RADAR TOPOGRAPHY MISSION AND LANDSAT DATA

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ABSTRACT. *Mangroves are one of the most productive forest ecosystems and play an important role in carbon storage. We examined the use of Shuttle Radar Topography Mission (SRTM) data to estimate mangrove Above-ground Biomass (AGB) in Sabah, Malaysia. SRTM-DEM can be considered as Canopy Height Model (CHM) because of the flat coastal topography. Nevertheless, we also introduced ground elevation correction using a Digital Terrain Model (DTM) generated with GIS and coastal profile data. We mapped the mangrove forest cover using Landsat imagery acquired in 2015 with the supervised classification method (Kappa coefficient of 0.81). Regression analyses of field AGB and the CHMs resulted in an estimation model with the corrected CHM as the best predictor (R^2: 0.73) and cross-validated Root Mean Square Error (RMSE) was 19.70 Mg ha^{-1} (RMSE%: 11.60). Our study showed Sabah has a mangrove cover of 268,631.91 ha with a total AGB of 44,163,207.07 Mg in 2015. This substantial amount of carbon storage should be monitored over time and managed as part of the climate change mitigation strategy.*

KEYWORD. Mangroves, SRTM-DEM, Landsat, Above-ground Carbon, Borneo.

INTRODUCTION

Mangrove forest is one of the most productive forest ecosystems in terms of its carbon cycling and storage (Pham and Brabyn, 2017). However, consistently high demand for natural resources, such as timber and fuel, and coastal land development have led to the destruction and degradation of mangroves (Kanniah *et al.*, 2015). Estimating and monitoring forest carbon stock are increasingly important in the context of climate change mitigation. Mangroves have great potential in both above and below ground carbon pools; storing up to five times more carbon per unit area than other forest ecosystems (Kauffman *et al.*, 2011; Stringer *et al.*, 2015). For the purpose of mangrove carbon stock monitoring, the estimation focuses more on the aboveground carbon or biomass (AGC/AGB) of mangroves (Shapiro *et al.*, 2015). The AGB stock estimation is done through an established allometry with field measurements. Although considered as accurate, it is impractical on a large spatial scale (Kauffman *et al.*, 2011) especially in areas with harsh conditions and difficult to access.

Remote sensing technology provides high-quality and consistent data over a long term at low cost per unit area (Kanniah *et al.*, 2015). It has been widely used to retrieve information of forests located in remote or inaccessible areas at a large-spatial scale. The Landsat Program provides free medium-resolution satellite imageries globally and has become the main data source of numerous studies related to tropical forest cover change monitoring (Giri *et al.*, 2011; Kirui *et al.*, 2013). On the other hand, Shuttle Radar Topographic Mission (SRTM) Digital Elevation Model (DEM) provides free and high-resolution digital elevation data that cover

80% of the Earth's land surface with 16 m absolute vertical height accuracy. Since SRTM-DEM correlates well with mangrove forest heights (Lagomasino *et al.*, 2016), it was used to estimate AGB of mangrove forests in various areas around the world (Fatoyinbo *et al.*, 2008; Fatoyinbo and Simard, 2013; Fayad *et al.*, 2016; Aslan *et al.*, 2016).

Sabah occupies more than half (58.6%) of Malaysia's mangrove forests (FAO, 2007), signifying the importance to evaluate the current distribution of mangrove cover and its current carbon storage potential. This study used medium-resolution satellite data to analyse mangrove forest cover for the year 2015 and to provide an AGB estimation model of mangrove forests in Sabah using SRTM-DEM.

MATERIALS AND METHODS

Field data collection

Location of field data collection was in the Northern part of Borneo Island especially West Coast of Sabah (5°25'13.45" N, 116°47'48.42"E) (Figure 1). Field inventory was conducted between August and October 2016. A total of 18 plots with square plot design (10 m × 10 m) and 24 plots with circular plots design (7 m radius) were established. A GARMIN GPSMAP 60 CSx was used to record the plot coordinates. The diameter at breast height (DBH) and tree height were measured for all trees with DBH > 5 cm. AGB was calculated from the field data using the allometric equation model developed by Saenger and Snedakar (1993):

$$AGB = 10.8H + 34.9 \quad (1)$$

Where AGB is aboveground biomass in Mg ha^{-1} and H is the tree height in meters.

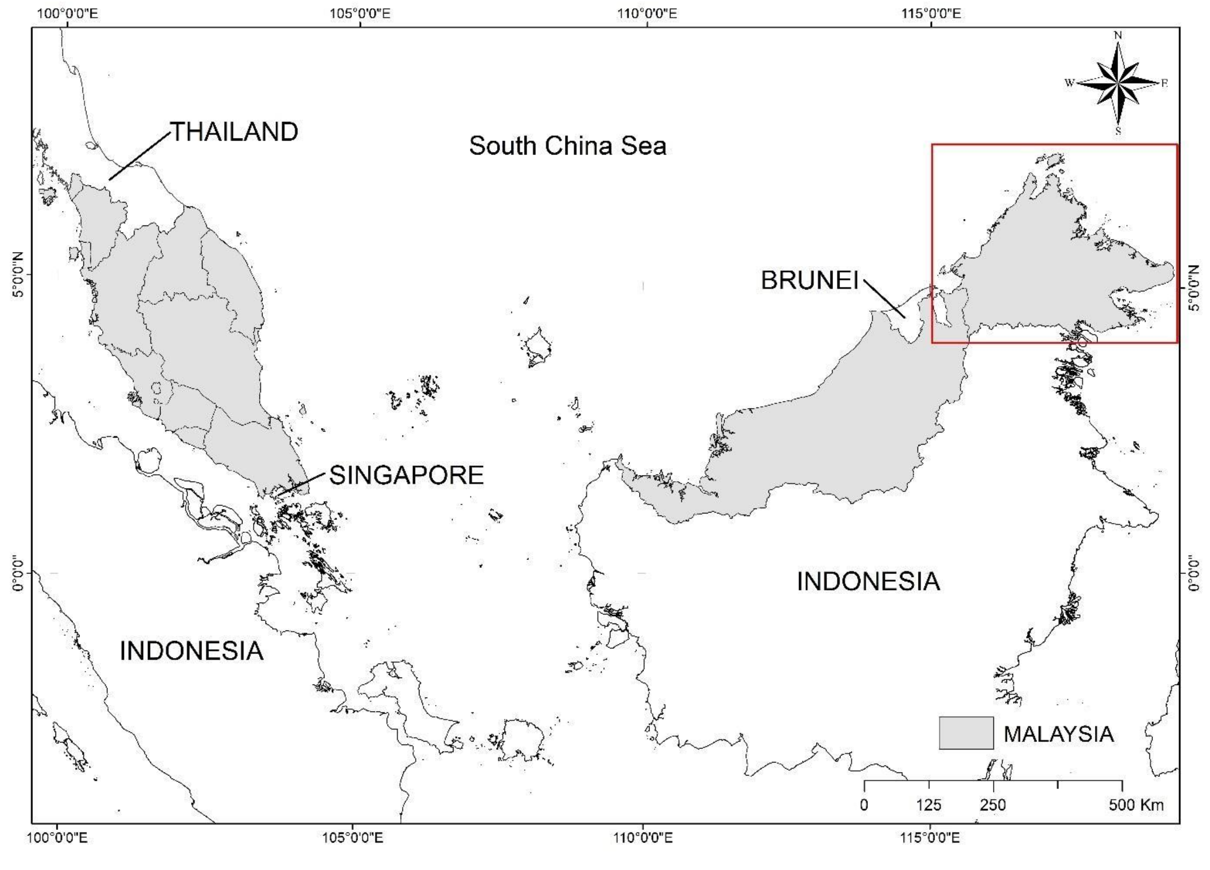

Figure 1: Location of study area

Landsat data acquisition and processing

Landsat imageries from Landsat 7 ETM+ and Landsat 8 OLI for year 2015 were downloaded from the United States Geological Survey (USGS) Center for Earth Resources Observation and Science (EROS) website (www.glovis.usgs.gov). To produce a full image mosaic of Sabah, multiple Landsat imageries from year 2014 to 2016 with different frames (Path/Row: 116/56; 116/57; 117/55; 117/56; 117/57; 118/55; 118/56; 118/57) were used. All images were reflectance (digital number to top-of atmosphere) and atmospherically (dark object subtraction) corrected. Removal of clouds and cloud shadows were done using Fmask software (Zhu and Woodcock, 2012).

The images were classified using supervised (Maximum Likelihood) classification. A total of 7 land cover classes were defined based on visual interpretation (water, mangrove, forest, agriculture, plantation, grassland and bare land). The classification accuracy was assessed using error matrix that includes producer accuracy, user accuracy, overall accuracy and Kappa coefficient. Google historical imageries from year 2014 to 2016 were used as reference data for 'ground-truthing' of the classification (301 points).

The Fmask software was only able to detect approximately 90% of clouds and cloud shadows. Thus, further classification of cloud and cloud shadow were done and removed during post-processing. Majority filtering (3 × 3) was then applied to the classified images to reduce the 'salt and pepper' effects. Pixels that were easily recognised were excluded (e.g. mangroves only grow near coastal area and inter-tidal zones and do not grow far inland and on highlands (Giri *et al.*, 2011)) to reduce misclassification. All images were mosaicked to generate a single raster of land cover classes and mangrove class was extracted for further analysis of AGB.

Shuttle Radar Topographic Mission digital elevation model (SRTM-DEM)

The SRTM-DEM data can be considered as Canopy Height Model for coastal mangroves (CHM_{mg}) because of the flat coastal topography and height estimation by radar is roughly the mangrove canopy heights (Simard et al., 2006; Fatoyinbo *et al.*, 2008). The CHM was corrected using a Digital Terrain Model (DTM) to improve the mangrove AGB estimation model (equation 2).

$$Corrected\ CHM_{mg} = SRTM\ DEM_{mg} - DTM_{mg} \quad (2)$$

As coastal elevation increases towards inland areas, the relationship between distance from coastline and elevation above mean sea level was established to generate the DTM_{mg}. A linear model was derived from six coastal profiles (obtained from the Sabah Shoreline Management Plan) (DHI Water and Environment, 2005) as follows;

$$DTM_{mg} = 0.0191D + 0.3427 \quad (3)$$

DTM_{mg} is ground elevation in meter (a.s.l) for mangrove and D is the distance from coastline in meters. The coastal profiles showed that ground elevation was constant after 200 m from the coastline. Thus, pixels less than 200 m from the coastline were used to generate the DTM_{mg} and the SRTM-DEM values were subtracted with the maximum value of DTM_{mg} for pixels more than 200 m from the coastline according to equation (2).

Statistical Analysis

Average values of pixels overlapping the plots for both CHMs were extracted and depicted as independent variables. The dependent variable (mangrove field AGB) was linearly regressed against both CHMs. Tree height is known to have nonlinear (i.e. multiplicative) relationship with AGB (Basuki *et al.*, 2009), thus, the variables were natural-log transformed. The estimation models were evaluated using R squared (R^2), root mean square error (RMSE) and relative RMSE (RMSE%) from the cross validation of estimated AGB and field-measured AGB. Leave-one-out cross-validation was used to calculate RMSE to prevent overfitting of the model.

RESULT

Land Cover Classification and Mangrove Forest Distribution

The land cover classification had an overall accuracy of 83.72 with *kappa* coefficient of 0.81 (Table 1). Reference data (301 points) were interpreted on Google Earth historical images to compare with the classified land cover classes. The mangrove class was extracted from the land cover classification. Based on the classification, mangrove area in Sabah was 268,631.91 ha in 2015.

Table 1: Error matrix of land cover classification.

		Groundtruth Point							Grand Total	**User's Accuracy, %**
		Water	Mangrove	Forest	Agriculture	Plantation	Grassland	Bareland		
Classified Point	Water	42	5		1			1	49	**85.71**
	Mangrove	5	57	1					63	**90.48**
	Forest	1	1	45	1	7			55	**81.82**
	Agriculture	1	1		9		1	1	13	**69.23**
	Plantation	2			2	43	3	1	51	**84.31**
	Grassland		1	1			16		18	**88.89**
	Bareland	5	2		3	1	1	40	52	**76.92**
	Grand Total	56	67	47	16	51	21	43	**301**	
Producer's Accuracy, %		**75.00**	**85.07**	**95.74**	**56.25**	**84.31**	**76.19**	**93.02**		
Overall Accuracy = 83.72; Overall Kappa = 0.81										

Aboveground Biomass Estimation

Table 2 shows the plot-level descriptive statistics of the mangrove forests characteristics. The average DBH and height was 10.82 cm and 11.38 m respectively. The shortest tree was found at Tuaran area (4.00 m) while the tallest tree was found in the northern part of Sabah (27.60 m). Forest stand height measured for individual trees within the plot were aggregated to generate plot-level AGB for all plots. The mangrove AGB ranged between 135.98 Mg ha^{-1} to 289.78 Mg ha^{-1}, with an average of 169.83 Mg ha^{-1}.

Table 2: Summary of field measurements.

	Average	Maximum	Minimum	Standard Deviation
DBH (cm)	10.82	49.00	5.00	5.59
Height (m)	11.38	27.60	4.00	3.19
AGB (Mg ha^{-1})	169.83	289.78	135.98	33.83

All 42 plots were used in the regression analyses between the CHMs and field AGB. The results (Table 3) showed that the model with Ln AGB as the dependant variable and corrected CHM_{mg} as the independent variable had the highest R^2 (0.73) with cross-validated Root Mean Square Error (RMSE) of 19.70 Mg ha^{-1}, which was only 11.60% of the average AGB. Figure 2 shows the scatter plot of field AGB and estimated AGB. This model was then used to produce estimated AGB of Sabah for the year 2015 (44,163,207.07 Mg).

Table 3: AGB estimation model using CHMs of SRTM.

	Variables	R	R^2	Model Equation	RMSE Mg ha^{-1}	% RMSE
Corrected CHM_{mg}	CHM - AGB	0.83	0.69	AGB= 7.09(CHM)+108.45	20.35	11.98
	Ln CHM -AGB	0.77	0.59	AGB= 56.08(Ln CHM)+54.62	23.43	13.80
	CHM - Ln AGB	**0.85**	**0.73**	**AGB= Exp (0.04 (CHM) + 4.79)**	**19.70**	**11.60**
CHM_{mg}	CHM - AGB	0.83	0.68	AGB= 5.64(CHM)+114.31	20.56	12.10
	Ln CHM -AGB	0.75	0.56	AGB= 48.43 (Ln CHM)+65.38	24.13	14.21
	CHM - Ln AGB	0.85	0.72	AGB= Exp (0.03 (CHM) + 4.82)	19.76	11.63

Note: Model in bold was the best model with lowest RMSE or RMSE%

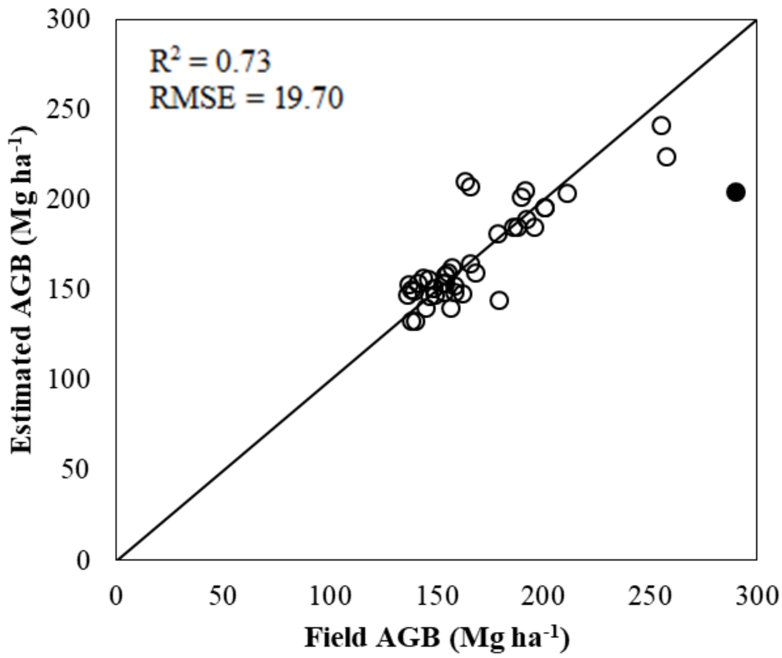

Figure 2: Field AGB VS estimated AGB. Only 1 plot (solid circle) had considerably underestimated the AGB

DISCUSSION

This study used supervised classification of Landsat imageries to obtain each land cover information for the year 2015. Although the classification accuracy showed good overall results, we were unable to classify the entire state of Sabah which affected the total areas of the classes assessed. Furthermore, comparison of each class area with existing literature was difficult due to the limited number of past studies. This study discusses primarily on mangrove forest covers. Mangrove areas obtained from this study was lower than reported by the Sabah Forestry Department in 2016 at 340,000 ha and the 2011 USGS Global mangrove dataset (Giri *et al.*, 2011) (http://data.unep-wcmc.org/datasets/4) at 284,952.27 ha. The lower values of mangrove areas estimated in this study could be due to higher percentage of cloud covering the mangrove area on the satellite images, especially in the coastal areas. In addition, the medium spatial resolution of Landsat imageries can limit the detection of mangrove areas that are partially submerged in coastal waters (Kirui *et al.*, 2013).

Studies in Kota Marudu (Sabah) and in Lawas (Sarawak) reported lower values of mangrove average field AGB (98.40 Mg ha^{-1} and 116.79 Mg ha^{-1} respectively) (Faridah-Hanum *et al.*, 2012; Chandra *et al.*, 2011) compared to our study. The variation in values may be due to the type of sampling technique, selection of allometric equation and environmental factors (plant density and plant growth rate) (Chandra *et al.*, 2011). Both past studies included trees with DBH > 1 cm while our study measured trees with DBH > 5 cm. Since we focused on AGB estimation over a large spatial scale, our sampling was sufficient enough for AGB estimation. Nevertheless, the average AGB in this study falls within the average AGB in Malaysia (172.9 Mg ha^{-1}) (Simard *et al.*, 2019).

Tree DBH has always been used in studies relating to AGB since it is easier to measure than tree height. However, preliminary tests using DBH-based equations resulted in higher RMSE. Since this study focuses on generating AGB from CHM, the height-based equation was used as it is the most common equation relating canopy height and mangrove AGB (Fatoyinbo *et al.*, 2018). The outlier plot in this study may be due to SRTM data error or changes during the 15-year gap between the field and SRTM data. Furthermore, relatively weak GPS signals (especially hand-held GPS) make it difficult to determine plot location accurately, which may increase the AGB estimation errors (Simard *et al.*, 2006; Fatoyinbo and Amstrong, 2010).

Although mangrove AGB estimation using remote sensing have been widely studied, very few have been done in Malaysia. The estimation of mangrove AGB in Peninsular Malaysia using ALOS PALSAR was done in Matang Mangrove Forest Reserve though their RMSE was higher than our study. It is possible that backscattering saturation occurred due to the limited penetration of synthetic aperture radar in dense forest canopy (Kugler *et al.*, 2014). To the best of our knowledge, there is no other study in Malaysia that estimates mangrove AGB using SRTM-DEM. This study showed that corrected CHM was the best predictor of mangrove AGB in Sabah, which slightly improved the mangrove AGB estimation compared to the CHM without correction using DTM.

CONCLUSION

This study successfully determined mangrove areas for the year 2015 using classification of medium resolution satellite images, and can be further investigated with multiple years to study the changes of mangrove areas. The AGB estimated in this study used correction of CHM together with field data. Since its acquisition in the year 2000, various satellite data other than SRTM-DEM are available and can be used to estimate mangrove canopy height more accurately. This study shows the potential of remote sensing data to estimate mangrove area and AGB and can be further used for monitoring the rate of changes of mangroves not only in the state but also at the national level.

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CONFLICT OF INTEREST

Authors declare that they have no conflict of interest.

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