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ESTIMATING ABOVE GROUND BIOMASS IN HILL DIPTEROCARP FOREST, KELANTAN, MALAYSIA USING LANDSAT 8 OLI

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ABSTRACT

Above ground biomass estimation for hill dipterocarp forest has received much attention in recent years because the change of biomass regionally is associated with important components of climate change. Accurate biomass estimation is necessary for better understanding of deforestation impacts on global warming and environmental degradation. This paper aims to develop allometric equations to estimate biomass in hill dipterocarp forest using satellite image Landsat 8 OLI. This study was executed in three different Permanent Reserved Forests (PRF) in Kelantan namely Bukit Bakar Recreational Forest (BB), Gunung Basor Forest Reserve (GB) and Gunung Stong Forest Reserve (GS). A total of 39 sampling plot were established. Regression analysis were used to developed several models. Model with NIR band is known to be the best model to estimate above ground biomass.

Keywords: above ground biomass, hill dipterocarp forest, above ground biomass, Band 5(NIR).

1. INTRODUCTION

1.1 Background of study

Vegetation cover or forest acts as major pool of carbon which is directly related to biomass productivity. The amount of biomass can give an estimation of global carbon stock, where by monitoring the changes of biomass we can measure carbon loss in the atmosphere. It is essential to estimate or calculate the biomass productivity for evaluating forest ecosystem production and controlling carbon budgets (Zianis and Mencuccini, 2004; Hall *et al.,* 2006). Gathering an information from aboveground biomass (AGB) will help the researcher to understand more about climate changes also help them to established carbon cycles model (Global Climate Observing System (GCOS) 2006).

Remote sensing was known with it's capability to monitor and gather the data at a large scale, manage to capture the variability of the land surface, offer a repeatability of data collection which help researchers conduct a time series data analysis. The signals used to capture the information are sensitive towards vegetation structure such as vegetation cover, density, shadow and texture (Baccini *et al*. 2008) which these parameter are related with AGB. Combination of these parameter with empirical models, was a common ways to estimate AGB. By using regression, a relationship may exist between spectral reflectance or vegetation indices and biomass (Foody *et al*., 2003; Lu *at al*., 2004; Okuda *et al* 2004).
There are many optical remote sensing satellite that are freely distributed with broadband multispectral sensor such as Landsat dataset. These datasets can estimate timely and regional scale AGB or carbon estimation (Gibbs *et al*., 2007;

Hall *et al*., 2011; Houghton *et al*., 1996; Vaglio Laurin *et al* 2014) and sustainable forest resources controlling and inventory (Næsset, 2007). The latest version in Landsat family is Landsat 8 Operational Land Imager (OLI) multispectral sensor where promise to deliver a number of helpful information for understanding regional influence of forest ecosystem to the carbon cycle (Dube and Mutanga, 2014). New improvement multispectral Landsat 8 sensor provide (i) enhance spectral range for certain bands that is crucial for improving the vegetation spectral response in near infrared (NIR) and panchromatic band, (ii) upgrade radiometric resolution from 8 bits to 12 bits which is very helpful in the characterization of diverse forest form (El-Askary *et al*., 2014; Pahlevan and Schott, 2013).

Numerous studies have shown that indices such as normalize difference vegetation index (NDVI), spectral vegetation index (SVI) and simple ratio (SR) calculated using satellite data were useful to estimate leaf area index (LAI), biomass and productivity in grassland and forest (Cheng and Zhao, 1990; Diallo *et al*., 1991; Fassnacht *et al*., 1997; Steininger, 2000). Yet, the result using this biophysical evaluation in tropical forest are inconsistent. Earlier studies found that these indices could not be used to calculate this parameter (Lu et al., 2004; Sader *et al*., 1989) while others found that it is significantly correlated with AGB (Gonzalez-Alonso *et al*., 2006; Zheng *et al*., 2007). These conflicting results occur due to saturation of the NDVI value at high biomass levels (Mutanga and Skidmore, 2004; Okuda *et al*., 2004) also poor atmospheric condition (Huete *at al*., 1994; Xiao *et al*., 2003).

In this study, we evaluated the result from this medium resolution multispectral Landsat 8 OLI in its ability to estimate forest AGB using different set of spectral analysis: spectral bands, spectral vegetation indices, spectral band with spectral vegetation indices. The objective of this study was to estimate above ground biomass in hill dipterocarp forest, Kelantan, Malaysia.

2. MATERIALS AND METHOD

2.1 Study sites

This study was executed in three different permanent reserved forests in Kelantan, Malaysia namely Bukit Bakar Recreational Forest (BB), Gunung Basor

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Forest Reserve (GB) and Gunung Stong Forest Reserve (GS). Generally, the vegetation type of these three PRFs was mainly hill dipterocarp forest at elevation between 300 to 750 m a.s.l.

2.2 Data collection

A total number of 30 random sample plots were established from Bukit Bakar Recreational Forest (BB), Gunung Basor Forest Reserve (GB) and Gunung Stong Forest Reserve (GS). Global Positioning System (GPS) was used to record the coordinates of plots. These plots were used to develop new allometric equation. Diameter at breast height (DBH) of trees were measured above the buttresses of tree (Basuki, 2012; Chave *et al*., 2014). Trees with DBH at least 10 cm in each plot were considered as sample. (Basuki, 2012; Heng and Tsai, 1999; Samalca, 2007). Physical characteristics were recorded and specimens collected for identification.

Above ground biomass (AGB) for each trees was carried out by adopting the allometric equation developed by Kato *et al* (1978). This equation used DBH as independent variable. The equation to estimate AGB was:

$$Y=0.2544*(DBH)\ 2.3648$$

where;
Y = AGB
DBH = Diameter Breast Height

2.3 Satellite data

The study area is lies in 2 Landsat tile, first tile path: 127, row: 56 and another tile path: 127, row: 57. Landsat Data Continuity Mission (LDCM)'s Landsat 8 OLI satellite images covering the region of interest which is Bukit Bakar Recreational Forest (BB), Gunung Basor Forest Reserve (GB) and Gunung Stong Forest Reserve (GS) were acquired on 2 April and 5 May, 2014. The images were acquired during a sunny and clear sky day conditions with less than 10% cloud cover and were downloaded from the USGS Earth Resources Observation and Science (EROS) Center archive (http://earthexplorer.usgs.gov/). The Landsat 8 OLI sensor was launched on the 11th of February 2013 with 16-day temporal resolution. On board the Landsat 8 OLI sensor, there are two pushbroom instruments: (i) the Operational Land Imager (OLI) comprising of nine spectral bands, see Table-1, and (ii) the Thermal Infrared Sensor (TIRS) which contains thermal bands 10 and 11 at a 100 m spatial resolution.

2.4 Image processing

A number of processing and pre-processing applied on the images. Atmospheric and haze correction were done in image pre-processing part. The data then been resample from 30m to 15m ground distance sampling (GDS) using Gram-Schmidt algorithm via pan sharpening tool in ENVI 5.1 processing package. Landsat 8 OLI was obtained in digital number (DN), thus it is essential to convert the DN values into reflectance values. Conversion from DN to reflectance was executed following the approach described on the USGS website (http://landsat.usgs.gov). These images were geo-rectified to UTM WGS 84, Zone 47.

2.5 Spectral indices

Numerous researchers have included spectral indices such as NDVI, Simple Ratio, Soil Adjusted Vegetation Index, Enhance Vegetation Index, Modified Soil Adjusted Vegetation Index and Adjusted Vegetation Index into their research to calculate AGB (Nssoko, 2007; Wijaya *et al*., 2010). In this study, we used reflectance band 1 to 7 and moisture vegetation indices (MVI) based on combination of reflectance band 5 and 6 (MVI6) and combination of band 5 and 7 (MVI7). These input parameter were chosen to estimate AGB because they had a better performance for biophysical valuation in other tropical forest (Freitas et. al., 2005; Lu et. al., 2004; Steininger, 2000; Tangki and Chappel, 2008). The formulas for moisture vegetation indices of MVI 6 and MVI7 as follows:

$$MVI6 = (NIR - MIR6) / (NIR + MIR6)$$
$$MVI7 = (NIR - MIR7) / (NIR + MIR7)$$

Where

MVI6 = Moisture Vegetation Index for band 5 and 6
MVI7 = Moisture Vegetation Index for band 5 and 7
NIR = Near Infrared reflectance (band 5) of Landsat 8 OLI
MIR6 = Middle Infrared reflectance band 6 of Landsat 8 OLI
MIR7 = Middle Infrared reflectance band 7 of Landsat 8 OLI

Table-1. OLI spatial characteristics. Source: http://landsat.usgs.gov.

OLI spectral bands		
Band	**Bandwidth** (μm)	**Ground distance sampling** (m)
1	0.433 – 0.453	30
2	0.450 – 0.515	30
3	0.525 – 0.600	30
4	0.630 – 0.680	30
5	0.845 – 0.885	30
6	1.560 – 1.660	30
7	2.100 – 2.300	30
8	0.500 – 0.680	15
9	1.360 – 1.390	30

2.6 Data analysis

Regression models of biomass were developed using field surveys variable (AGB) and independent variables namely spectral band 1(coastal aerosol), band 2(blue), band 3(green), band 4(red), band 5(NIR), band

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6(SWIR1), band 7(SWIR2) and vegetation indexes (MV16 and MV17) that derived from Landsat 8. Before develop model, Pearson correlation coefficient was used to determine the strength and direction of relationship between AGB data with spectral bands and vegetation indexes. Then, regression analyses were conducted to develop several regression equations between AGB with stronger correlation variables. Prior establishing the analyses, data exploration was carried out to get models that best fit the data. Scatter plots were used to determine whether linearity exist (Basuki, 2012) between AGB with independent variables. Since only some of the assumptions of regression met, we transformed the data for linear regression (Addo-Fordjour and Rahmad, 2013; Chave *et al*., 2014; Samalca, 2007) using natural logarithm. Natural logarithm of the dependent variable (AGB) and independent variables were found to be the best transformations which produced models that did not violate regression assumptions.

Selection of models for estimating the AGB were based on coefficient of determination (R2) (Basuki, 2012; Lu *et al*., 2012; Singh, Malhi, and Bhagwat, 2014) and significant value (p-value) of F-statistics. (Gasparri, Parmuchi, Bono, Karszenbaum, and Montenegro, 2010).

3. RESULTS AND DISCUSSIONS

For a better interpretation of remote sensing data in the study area, Table-2 summarizes descriptive statistics of the AGB of the 30 sampling plots. The average of AGB in field sampling is 1498.19 ton/ha. Table-3 shows the correlation coefficients (r) between spectral bands, vegetation indexes with AGB. It can be seen that band 5(NIR) has strongest correlation with the AGB ($r=0.721$, $p<0.001$) followed by band 6(SWIR1), 1 (coastal aerosol) and band 2(blue). For the vegetation indexes, there are no significant relationships with AGB. These two independent variables were not used to generate model. Therefore, four bands (1, 2, 5 and 6) were used to generate regression models to predict the AGB. Gasparri *et al*., (2010) in their study found stronger correlations for bands 2, 3, 5, 7, NDVI and NDMI with AGB in subtropical dry forest of Argentina. The different forest type could be the reasons for the different results of correlation analysis.

Table-2. Descriptive statistics of AGB.

Descriptive statistics	Above ground biomass (ton/ha)
Minimum	503.33
Mean	1498.19
Maximum	3700.87
Std. Deviation	721.81

Table-3. Correlation analysis.

Landsat 8			Vegetation		
Band	Pearson correlation	p-value	Band	Pearson correlation	p-value
1	-.521	.000	MV16	-.019	.915
2	-.528	.000	MV17	.122	.484
3	-.323	.000			
4	-.480	.000			
5	.721	.000			
6	.599	.000			
7	.462	.042			

Table-4 reveals statistical analysis of the regression models. A total of 6 models were generated to estimate above ground biomass. Model 1, 2 and 4 produced overall 0.30 coefficient of determination. While model 3 and 6 (combination band 1, 2, 5 and 6) provide 0.51 and 0.49 respectively. The best model was a single band model using band 5 (Model 3). Band 5(NIR) explained 51% of variance in AGB. This coefficient of determination is lower than that obtained by Basuki (2012) and (Zheng *et al*., 2004) with 63% and 82% respectively. The p-value indicates that band 5(NIR) is significantly related to AGB. NIR band is known to be a better indicator of above ground biomass. NIR has high sensitivity in detecting healthy plants. The water in their leaves scatters the wavelengths back into the sky. This study does agree with previously research by Asner (1998) in savannas and woodlands in Mexico and Brazil. But this departure with Gasparri *et al*., (2010), they found the effect of bare soil in the sparse dry forest may have reduced the accuracy to estimate AGB.

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Table-4. Regression models between spectral bands (spectral reflectance of Landsat 8 OLI) and the AGB using 39 plots.

Model	Independent variable	Equation	R^2	p-value
1	Band 1	Ln(AGB)= -5.163 - 5.190*Ln(Band 1)	0.252	0.000
2	Band 2	ln(AGB)= -4.174- 4.338*Ln(Band 2)	0.278	0.000
3	Band 5	ln(AGB)= 14.451 - 5.149*ln(Band 5)	0.507	0.000
4	Band 6	ln(AGB)= 14.087 - 3.014*ln(Band 6)	0.341	0.000
6	Band 1,2,5,6	ln(AGB)= 8.493 - 15.788*ln(Band 1) + 12.250* ln(Band 2) +5.390*ln(Band 5) – 0.357* ln(Band 6)	0.490	0.000

4. CONCLUSIONS

The result shows that Model 3 is the best model with the highest coefficient of determination. The proposed model reveals Band 5(NIR) increased the estimation accuracy of AGB in Hill Dipterocarp forest, Kelantan. Due to NIR has high sensitivity in detecting healthy plants, we can conclude that the forest in Kelantan is highly contributes to biomass and carbon stock that important for ecology.

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