Abstract No: A-177

COMBINATION OF PALSAR-2 AND SPOT-6 IMAGES FOR ESTIMATING ABOVEGROUND BIOMASS OF PEAT SWAMP ECOSYSTEM IN MALAYSIA

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SUMMARY

Aboveground biomass (AGB) is one of the key parameters important for carbon accounting in a forest ecosystem. However, estimating this parameter by using remote sensing approach has been challenging as it is constrained by various limitations, especially in tropical region. Spaceborne optical and radar systems have the potential in obtaining AGB reliable estimates but several issues such as cloud cover, dense and complex stand structure, and saturation of signals at certain biomass level still remain unanswered. Peat swamp forest, one of the forest types in Malaysia, is centric as it known to store a large amount of biomass carbon and plays a significant role in balancing terrestrial carbon cycle. A study was conducted to investigate the possibility of combining both optical and radar to improve accuracy of AGB estimation in the peat swamp forest. Optical Satellite Pour l'Observation de la Terre (SPOT-6) and Phased Array type L-band Synthetic Aperture Radar (PALSAR-2) data that have been acquired in year 2015 were used in this study. Peat swamp forest in Pekan, Pahang which is the biggest patch of peat swamp forest in Peninsular Malaysia was selected as the study area. It covers 107,203 ha comprised entirely of peat swamp forest. A number of sample plots were established on the ground and the AGB was measured. Regression models were produced correlating the measured AGB and several variables derived from both satellites data. The study found that the best performing regression model was from the combined modified vegetation-water index (MVWI) with horizontal-vertical (HV) polarized backscatter. The combination of optical and radar systems data has countered limitations of each other and improved the estimate. This approach was therefore suggested to obtain better accuracy in estimating AGB in a large area of peat swamp forest.

Keywords*: Peat ecosystem, aboveground biomass, remote sensing*

INTRODUCTION

Peat swamp forest and its ecosystem play a significant role in the climate change because they serve as sinks of carbon and store carbon more compared to other forests. Due to the rising climate change issue, the information on peat swamp forest is become vital. There are also interest and rapidly increasing need on carbon stocks (and CO_2) information at a national level in line with international initiatives such as Kyoto Protocol (1997), Reducing Emissions from Deforestation and Forest Degradation and forest conservation (REDD+) (2007), host by United Nations Framework Convention on Climate Change (UNFCCC) and national policies related to climate change (National Forestry Policy (1978), National Energy Policy (1979), National Policy on Biodiversity (1998), National Policy on Environment (2002). Among others, REDD+ program is now is attracting most attentions from the governments including Malaysia.

However, the question of how to measure carbon stock in the forests as well as carbon emissions resulted from the deforestation are crucial and should be answered before the REDD+ can be implemented. There is a tradeoff between the cost and the accuracy of the methods. In some countries, the need for a high level of precision requires the use of fine-resolution remote sensing imagery (e.g. to detect forest degradation or small-scale deforestation), imagery repeated over time (e.g. to overcome cloud cover limitations) or imagery that requires significant expertise to process (e.g. analyzing radar images), all of which come at a cost. Similarly, ground measurements, crucial to verify and measure carbon stocks, are time consuming and relatively expensive at a large scale, such as a national inventory (Gibbs *et al.* 2007).This project is therefore proposed as an initial idea to examine the use of remote sensing technology in providing carbon stock information with optimized cost and accuracy.

In many parts of the world, especially in tropical region, the frequent cloud conditions often restrain the acquisition of high-quality remotely sensed data by optical sensors. The acquisition of cloud-free, wall-to-wall optical satellite images in tropical countries is almost impossible (Hamdan *et al*. 2014a). Thus, synthetic aperture radar (SAR) data become the only feasible way of acquiring remotely sensed data within a given timeframe because the SAR systems are independent of cloud coverage, weather and light conditions. Due to this unique feature compared with optical sensor data, the SAR data have been used extensively in many fields, including forest-cover identification and mapping, discrimination of forest from other land covers and forest biomass estimation (Hamdan *et al.* 2015).

In the context of biomass estimation, optical systems have been facing problems and limitations in tropical forests (Asner 2001; Lu 2006). It has been proven that spectral reflectance and vegetation indices alone are not reliable indicators of biomass in tropical forests and that the direction of their relationship was also inconsistent (Foody *et al.* 2003). Spectral reflectance was also not sensitive to the spatial variation of biomass higher than 150 Mg ha^{-1} (Steininger, 2000). The poor performance of optical remote sensing methods in the tropics has been mainly attributed to the multi-layered closed canopy structure of tropical forest.

SAR, on the other hands estimates biomass in different manner. The capability of SAR system to penetrate through the canopy has contributed to the advancements of modern forestry. Among many SAR systems available, L-band has the most potential for forest biomass estimation as it carries mainly information about larger components of vegetation such as trunks and branches (Wolter and Townsend, 2011). While L-band SAR system offers some advantages in estimating forest biomass, the saturation problem is common in the data. It means that the sensitivity of the returned signal (i.e. backscatter intensity) will cease at certain threshold of biomass. This has been identified as a critical challenge in the last decade (Shi *et al*. 2012). The saturation levels depend on the polarization and the structure of the forests such as the size, density and distribution of the branches and leaves (Hamdan *et al.* 2014b). The relatively low saturation level causes dramatic limitations on the applicability of radar methodology for biomass estimation in tropical forests that typically have high levels of biomass.

Several studies have shown that the integration of optical and SAR data for biomass estimation is promising due to the complementary strengths of the sensors. Studies (e.g. Hamdan *et al.* 2014c) also indicated that the range of validity of SAR signals can be extended by including optical data into canopy scattering models for biomass estimation. Multiple regression models were also used to estimate forest biomass for this purpose.

Realizing the importance of biomass estimation in the tropical forests as well as issues and limitations on the methodology, this study is therefore conducted. It aims to evaluate the capability of both optical and SAR systems in estimating aboveground biomass (AGB) of peat swamp forest in Peninsular Malaysia, simultaneously to investigate the synergy by integrating both of them.

MATERIALS AND METHODOLOGY

The Study Area

The study area is located at the south-east part of Pahang in Peninsular Malaysia. The south-east Pahang peat swamp forest (SEPPSF), located at Pahang state is the largest peat swamp forest complex in Peninsular Malaysia and is believed to be the mainland Asia's largest and intact peat swamp forest. It covers an area of 107,203 ha and comprises four Forest Reserves, namely Pekan, Kedondong, Nenasi and Resak. It harbors unique flora and fauna, provides benefits and services of national interest and supports the livelihood of the aborigines (Orang Asli) communities. Figure 1 shows the location of the study area.

Satellite Images

Two sets of satellites images, which are SPOT-6 and PALSAR-2 (Phased Array type L-band Synthetic Aperture Radar) onboard Advance Land Observing Satellite (Alos-2) were used in this study. Both images were acquired in year 2015. The SPOT 5 HRG image has a spatial resolution of 5 m and contained four wavelength bands; green (Band 1; 0.50 – 0.59 µm), red (Band 2; 0.61 – 0.68 µm), near infra-red (Band 3; 0.79 – 0.89 µm) and shortwave infra-red (Band 4; 1.58 – 1.75 µm). The digital numbers (DN) were first converted to top of the atmosphere (TOA) reflectance by using historical empirical line method (HELM) (Clark *et al.* 2010). For the PALSAR-2 data, the Level 1.5 Fine Beam Dual images were obtained from Japan Aerospace Exploration Agency (JAXA). It was a geometrically corrected and has a resolution of 6 m. The dual-polarized L-band images were converted from 16-bit digital number to the normalized radar cross section (NRCS) that read the data in backscattering coefficient also known as sigma-naught, with units in decibels (dB) (Shimada *et al.* 2009).

Methodology

There are two major activities involved in the study, namely ground data collection and satellite image processing. A total of 48 sampling plot were established in year 2014. All trees stands measuring diameter at breast height (dbh) of 10 cm and above were measured. The allometric function of trees and the calculation of aboveground biomass (AGB) was calculated based on mass per hectare, which gives the units of Mg ha^{-1}. Aboveground biomass comprises all the living aboveground vegetation, including stems, branches, twigs and leaves. It is the most important pool of carbon of all types of forests. In this study, allometric equation from Chave *et al.* (2005), which is specified for peat swamp forest types was adapted. The AGB of a tree can be expressed as

$$AGB = 0.65*\exp(-1.239 + 1.98*\ln(D)+0.207*\ln(D)^2-0.0281*\ln(D)^2 \quad (1)$$

where D is diameter at breast height (dbh) of the measured tree.

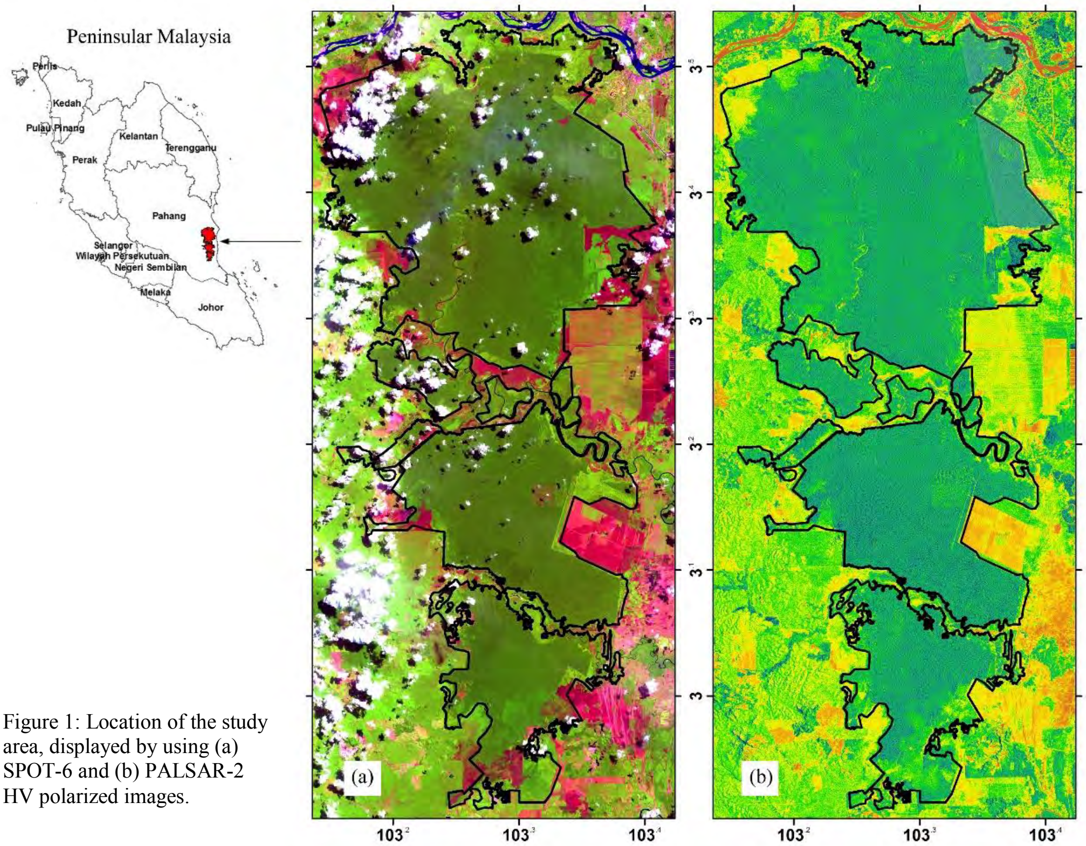

Figure 1: Location of the study area, displayed by using (a) SPOT-6 and (b) PALSAR-2 HV polarized images.

Several images variables were derived from both SPOT-6 and PALSAR-2 data and the pixel values extracted were correlated with the measured AGB on the ground. The microwave energy transmitted that penetrates the forest canopies is largely dependent on the size and orientation of canopy structural elements, such as leaves, branches and stems. It also depends on the polarimetry of the wave. PALSAR-2 has two polarizations, horizontal (HH) and vertical (HV) polarimetry. Studies e.g. Lucas *et al.* (2010); Hamdan *et al.* (2015) found that only HV responded well in estimating AGB of a natural forest. Therefore only HV polarization was used in this study to investigate their correlations.

SPOT-6 in the other hands was used to produce two indices, which are normalized difference vegetation index (NDVI) and normalized difference water index (NDWI). NDVI is a spectral indicator that is commonly used to detect and measure conditions of vegetation. Whereas NDWI is a satellite-derived index from the Near-Infrared (NIR) and Short Wave Infrared (SWIR) channels. The SWIR reflectance reflects changes in both the vegetation water content and the spongy mesophyll structure in vegetation canopies, while the NIR reflectance is affected by leaf internal structure and leaf dry matter content but not by water content. The combination of the NIR with the SWIR removes variations induced by leaf internal structure and leaf dry matter content, improving the accuracy in retrieving the vegetation water content (Ceccato *et al.* 2001). The amount of water available in the internal leaf structure largely controls the spectral reflectance in the SWIR interval of the electromagnetic spectrum. SWIR reflectance is therefore negatively related to leaf water content (Tucker, 1980).

These image variables in this study to predict the AGB. Instead of using the variables individually, a manipulation has been applied. A modified vegetation-water index (MVWI) has been produced from the NDVI and NDWI of the SPOT-6 images. This was then combined with HV backscatter from PALSAR-2 with exponential function to produce a new image variable, namely combined optical and SAR variable (COSV). All image variables that were used in the study is summarized in Table 1.3

Table 1: Summary of image variables used in the AGB predictions

Image Variables	Formula	Description	Source
NDVI	$\frac{\mathrm{NIR}-\mathrm{R}}{\mathrm{NIR}+\mathrm{R}}$	Normalized Difference Vegetation Index. Related to changes in amount of green biomass, pigment content and concentration and leaf water stress etc.	Huete (1988)
NDWI	$\frac{\mathrm{NIR}-\mathrm{SWIR}}{\mathrm{NIR}+\mathrm{SWIR}}$	Normalized Difference Water Index is a remote sensing based indicator sensitive to the change in the water content of leaves.	Gao (1996)
HV	PALSAR-2 HV	HV backscatter of PALSAR-2 sensor presented in sigma-naught values.	-
MVWI	NDVI × NDWI	Enhancement of normalized vegetation and water indices to extract plant component of peat swamp forest.	This study
COSV	$e^{(\mathrm{HV}*\mathrm{MVWI})}$	Combination of indices derived from optical data with PALSAR-2 HV polarization to enhance forest height and biomass of peat swamp forest.	This study

RESULTS AND DISCUSSION

The models used AGB as independent variable to observe the sensitivity of the backscattering coefficients to the AGB. The model was generally written in logarithmic form as $y=a\times ln(x)+b$, where x and y denote AGB and image variables, respectively.

The study has produced a number of models according to the image variables derived. All variables can be used for biomass estimation in the study area with certain degrees of accuracies. Obviously COSV that was derived from the combination of optical and SAR gave relatively higher coefficients of determination (R^2) with RMSE of about 52 Mg ha^{-1} compared to the other variables in a single regression. Table 2 summarizes the models that were produced with accuracies of the estimated AGB and Figure 2 show.

Table 2: Summary of linear regression models developed from the image variables.

Image variables	Model coefficient		R^2	RMSE (Mg ha^{-1})
	a	*b*		
NDVI	0.11211	- 0.2536	0.1429	98.76
NDWI	0.11811	- 0.4123	0.1233	93.21
MVWI	0.07261	- 0.3117	0.1552	71.42
HV	4.29740	- 39.015	0.2257	62.70
COSV	0.14561	- 0.7136	0.3653	51.94

Referring to the Table 2, the last model, which incorporated both SPOT-5 and Alos PALSAR images, surprisingly gave better accuracy compared to the use of SPOT-6 and PALSAR-2 variables alone. The R^2 has slightly increased and thus the RMSE has also decreased. It is therefore proven that the integration of optical and SAR systems could give a better accuracy and potential in estimating biomass in tropical forest. The effect of the combination was also appear on the image and can be seen clearly from visual interpretation as shown in Figure 3.

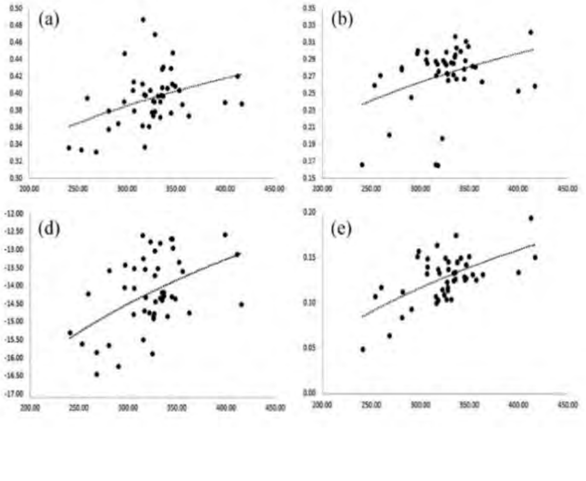

Figure 2: Scatterplots of the correlations between estimated AGB and images variables. (a) NDVI (b) NDWI (c) MVWI (c) HV backscatter (d) MVWI and (e) COSV.

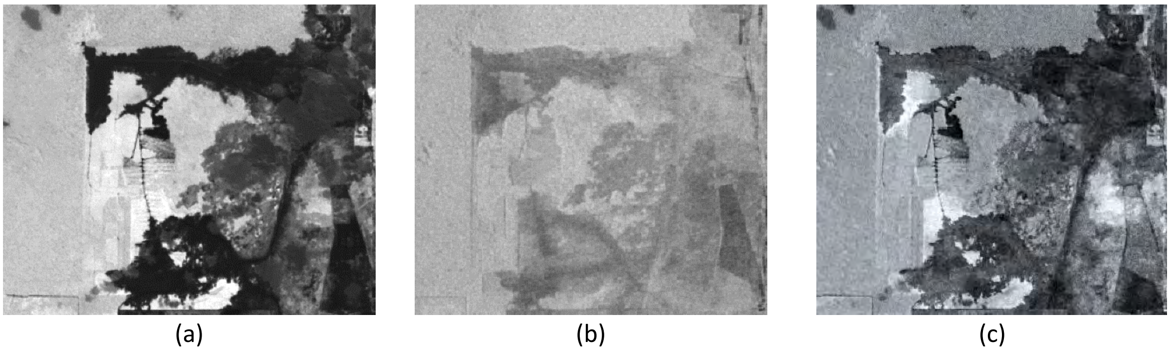

Figure 3: Image variables that were used for AGB prediction, which are (a) MVWI, (b) HV polarization, and (c) combination of MVWI and HV images. The enhancement technique has produced an image with more pixel variation that is able to represent real condition of trees composition on the ground.

The distribution and total AGB in the study area was estimated based on the best correlation model produced. It was found that the AGB in the study area ranged from 68 to 583 Mg ha^{-1} with an average of 352.47±51.94 Mg ha^{-1}. From these figures, it was estimated that the total AGB stored in the study area was about 37,785,841 Mg. The results were validated by using 8 independent plots to measure the overall reliability of the estimate. Figure 3 shows the scatterplots, which include the values of measured AGB on the ground against the predicted AGB from the estimation model. The result shows that the model has slightly underestimated the AGB. Finally, the model was used to produce a spatially distributed AGB in the study area as depicted in Figure 4.

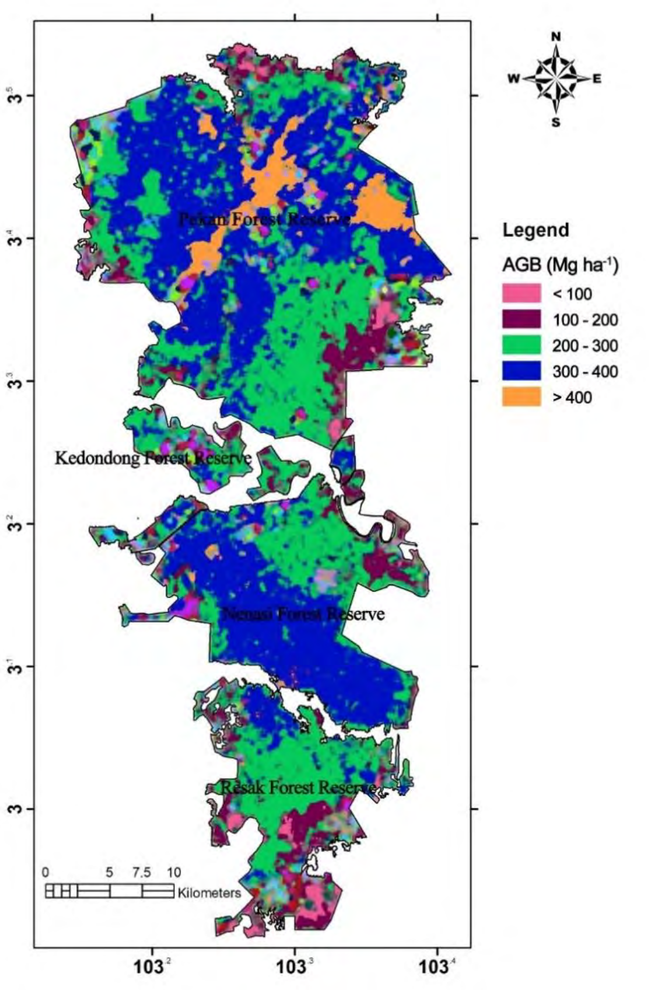

Figure 4: Spatially distributed map of AGB estimated in the study area.

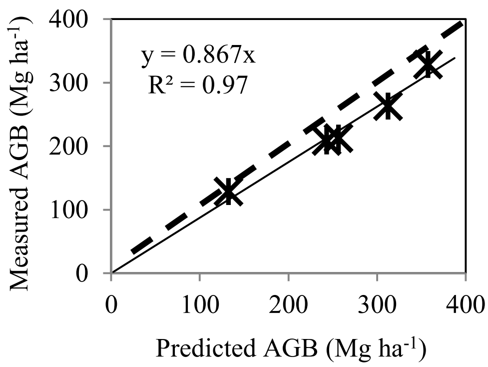

Figure 3: Correlation between measured and predicted AGB in five independent validation plots. The dashed line represents perfect agreement between measured and predicted AGB, indicating that the developed model has underestimated the AGB.

CONCLUSION

The study has successfully investigated the potential benefits that can be obtained from incorporating both optical and SAR systems in the forest biomass estimation. It was found that the combination of indices derived from SPOT-6 with backscattering from HV polarization of PALSAR-2 gave the best accuracy of estimation. Although the issue on saturation is not discussed in details in this study, the results indicated that the optical and SAR systems are compliment to each other, which have potential to overcome saturation problem. Both systems can play significant roles in estimating and monitoring biomass of tropical forest and are still relevant instead of advancements made in remote sensing technology. It is therefore suggested that a combination of optical and SAR remote sensing data supported by extensive field sampling can be used to monitor biomass in tropical forests. Empirically derived biomass estimation models combined with comprehensive sample plots would be of useful for monitoring purposes in REDD+ and other similar activities aiming to promote preservation of biomass in tropical forest ecosystems.

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