Combination of SPOT-5 and ALOS PALSAR images in estimating aboveground biomass of lowland Dipterocarp forest

O Hamdan13 I Mohd Hasmadi2 and H Khali Aziz1
1 Forest Research Institute Malaysia, 52109 FRIM, Kepong, Selangor, Malaysia
2 Faculty of Forestry, Universiti Putra Malaysia, 43400 Serdang, Selangor, Malaysia

Email: hamdanomar@frim.gov.my

Abstract. Aboveground biomass (AGB) of forests is the one of the key parameters for carbon accounting. However, estimating AGB by using remote sensing approach has been challenging as it is constrained by various limitations, especially in a complex tropical forest ecosystem. Optical or radar system has its potential in retrieving AGB but issues such as cloud cover, complex forest ecosystem and saturation at certain biomass levels remain unanswered and are continuously being studied. The study was conducted to investigate the possibility of combining both optical and radar to improve the accuracy of AGB estimation in lowland dipterocarp forest. SPOT-5 and ALOS PALSAR data were used and regression models were developed between the measured AGB and variables derived from both satellite images. The study found that the best performing model was from the multivariate regression from incorporating both normalized difference fraction index (NDFI) with HV-polarized backscatter with $R^2$ of 0.803 and RMSE of 32.6 Mg ha$^{-1}$. The study found that the combination of optical and radar images can counter limitations of each other and has improved slightly the estimate.

1. Introduction
Tropical forests are known to store larger amount of biomass then the other forest types found in the world. Peninsular Malaysia that has about 5.8 million ha of tropical forest stores a considerable amount carbon stock. Out of this, about 2.7 million ha falls under lowland dipterocarp forest. This type of forest is being central for local timber productions and wood extractions, where logging activities take place. The stock and changes of biomass in these areas are dynamic as the trees are selectively felled being sustainability considered.

Meanwhile tropical forests also play crucial roles in mitigating effects of climate change and control the global carbon balance [1]. It is often related to the carbon emission from deforestation and greenhouse gas emissions in current Reducing Emissions from Deforestation and Forest Degradation with additional forest conservation (REDD+) initiative in Developing Countries [2]. Deforestation and forest degradation have been identified as major contributors to global climate change producing nearly 20% of global anthropogenic greenhouse gas emissions [3]. Due to the high carbon content of vegetation biomass, accurate quantification and monitoring of forest biomass is necessary for evaluation of schemes aiming to reduce carbon emissions from changes in forest areas. Remote sensing has been recognized as one of the primary spatial inputs for this process [1],[4],[5]. Both optical and active remote sensing systems have been used for forest biomass estimation since the last

3 To whom any correspondences should be addressed.
few decades. These systems offer specific advantages, challenges and limitations for producing reliable estimate at given scales [6].

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 [7]. Thus, synthetic aperture radar (SAR) data become the only feasible way of acquiring remotely sensed data without clouds. 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.

In the context of biomass estimation, optical systems have been facing problems in tropical forests [6],[8]. 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 [9]. Spectral reflectance was also not sensitive to the spatial variation of biomass higher than 150 Mg ha$^{-1}$ [10]. The poor performance of optical remote sensing methods in the tropics has mainly been attributed to the multi-layered closed canopy structure of tropical forest.

SAR, on the other hand, 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 potential for forest biomass estimation as it carries mainly information about larger components of vegetation such as trunks and branches [5],[6],[11],[12]. 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 [6]. The saturation levels depend on the polarization and the structure of the forests such as size, density and distribution of the branches and leaves [11],[13]. 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 [12],[14]. Studies (i.e. [15],[16]) 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 [17].

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 lowland dipterocarp forest in Peninsular Malaysia, simultaneously to investigate the potential capability that can be obtained by integrating both of them.

2. Materials and Methodology

2.1. The Study Area

The study area is a small portion of the Dungun Timber Complex (DTC), Terengganu. It is located within 4.86 N, 103.01 E (upper left) and 4.78 N, 103.07 E (lower right). There are altogether ten compartments, which are four in West Pasir Raja and six in Jerangau Forest Reserves, made up 2,891 ha of lowland dipterocarp forest. Felling began as early as 1970 until 2010 with some compartments are now entering the second rotation, being the 30 year cutting cycle of the selective management system. However some compartments are still in natural condition where logging never occurred although the entire study area is meant for production purpose.
2.2. Satellite Images
Two sets of satellites images, which are SPOT-5 HRG (High Resolution Geometric) and ALOS PALSAR (Phased Array type L-band Synthetic Aperture Radar) were used in this study. Both images were acquired in year 2012 and 2010, respectively. The SPOT 5 HRG image has 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 converted to top of the atmosphere (TOA) reflectance by using historical empirical line method (HELM) [18]. For the ALOS PALSAR data, the Level 1.5 images that came with two polarizations, HH and HV were obtained from Japan Aerospace Exploration Agency (JAXA). It was a geometrically and topographically corrected and has pixel resolution of 25 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) [19].

2.3. Methodology
There are two major steps involved in the study, namely ground sampling and satellite image processing. Ten (10) sampling plots were established in early 2012. All trees stands measuring 5 cm of diameter at breast height (DBH) were measured but only trees with DBH 15 cm and above were included in the AGB calculation, as suggested by [20]. The allometric function of trees and the calculation of standing biomass were carried out according to [21]. The AGB was calculated based on mass per hectare, which gives the units of Mg ha\(^{-1}\). Several variables were derived from both SPOT-5 and ALOS PALSAR images that were correlated with the measured AGB on the ground. All image variables that were used in the study are summarized in table 1.

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. ALOS PALSAR has two polarizations, horizontal (HH) and vertical (HV) polarimetry. Studies (e.g. [11],[22],[23]) found that only HV responded well in estimating AGB. However both polarizations were used in this study to investigate their correlations. The sample unit, with pixel resolution of 100 x 100 m (1 ha) instead was used to derived an empirical prediction model to estimate AGB for the study area [24].
**Table 1.** Summary of image variables used in the AGB predictions.

| Image Variables | Formula | Description | Source |
|-----------------|---------|-------------|--------|
| NDVI            | \( \frac{IR - R}{IR - R} \) | Normalized Difference Vegetation Index. Related to changes in amount of green biomass, pigment content and concentration and leaf water stress etc. | [26] |
| SAVI            | \( \frac{NIR - R}{NIR + R + L} \times (1 + L) \) | Soil Adjusted Vegetation Index, used to minimizes soil brightness-induced variations. L= 0.5 is used to reduce noise introduced from soil. | [27] |
| EVI             | \( \frac{2.5 \times (NIR - R)}{(NIR + 2.4 \times R + 1)} \) | Enhanced Vegetation Index. | [28] |
| NDFI            | \( \frac{GV_{Shade} - (NPV + Soil)}{GV_{Shade} + (NPV + Soil)} \) where \( GV_{Shade} \) is the shade-normalized GV fraction given by \( GV_{Shade} = \frac{GV}{100 - Shade} \) | Where NPV is non-photosynthetic vegetation and GV is green vegetation (GV) included to enhance the ability to detect logging infrastructure and canopy damage. Soil is the soil fraction and all the parameters were obtained with Spectral Mixture Analysis (SMA). | [29] |
| HH              | Palsar HH backscatter | HH backscatter of ALOS PALSAR sensor presented in sigma-nought values. | - |
| HV              | Palsar HV backscatter | HV backscatter of ALOS PALSAR sensor presented in sigma-nought values. | - |
| HH x HV         | Multiplicative product of Palsar HH and HV backscatters | HH multiplied by HV backscatter of ALOS PALSAR data, unitless. | - |

3. Results and Discussion
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, NDFI and HV variables from SPOT-5 and ALOS PALSAR gave relatively higher coefficients of determination (R\(^2\)), with the same RMSE of about 42 Mg ha\(^{-1}\) compared to the other variables in a single regression. NDVI and EVI also gave reasonable estimates but limited by high RMSE of 43.8 and 51.4 Mg ha\(^{-1}\), respectively. Table 2 summarizes the models that were produced together with corresponding information on the accuracies of the estimated AGB.

Referring to the table 2, the last model, which incorporated both SPOT-5 and ALOS PALSAR images, was surprisingly gave better accuracy compared to the use of SPOT-5 and ALOS PALSAR variables alone. The R\(^2\) has increased from about 0.6 to 0.8, while RMSE decreased to about 10 Mg ha\(^{-1}\). This model was produced from multivariate regression analysis, which included both variables into a linear regression model. 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 study also found that the use NDFI has greatly improve the estimation compared to the other traditional vegetation indices such as NDVI, SAVI and EVI that can be produced commonly from optical imagery [25]. Manipulation of polarizations also did not promise any improvement in the estimate.

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 98 to 415 Mg ha\(^{-1}\) with an average of 226.7±35.6 Mg ha\(^{-1}\). From these figures, it was estimated that the total AGB stored in the study area
was about 655,389.7 Mg. The results were validated by using five (5) independent plots to measure the overall reliability of the estimate. Figure 2 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 underestimated about 12.6%. Finally, the model was used to produce a spatially distributed AGB in the study area as depicted in figure 3.

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

| Variables  | Model                          | R   | $R^2$ | Adjusted $R^2$ | RMSE (Mg ha$^{-1}$) |
|------------|-------------------------------|-----|-------|----------------|---------------------|
| NDVI       | 449.368* NDVI - 499.077       | 0.771 | 0.594 | 0.543          | 43.767              |
| SAVI       | 158.454* SAVI - 331.310       | 0.116 | 0.013 | 0.110          | 68.206              |
| EVI        | 327.521* EVI + 40.191         | 0.663 | 0.439 | 0.369          | 51.424              |
| NDFI       | 332.446* NDFI + 29.622        | 0.783 | 0.613 | 0.565          | 42.700              |
| HV         | 29.618* HV + 704.583          | 0.791 | 0.626 | 0.579          | 41.994              |
| HH         | 14.482* HH - 161.072         | 0.678 | 0.460 | 0.393          | 50.443              |
| HH x HV    | 1.035* (HH x HV) +160.310    | 0.599 | 0.358 | 0.278          | 54.997              |
| NDFI and HV | 19.425* HV+212.792* NDFI + 399.667 | 0.896 | 0.803 | 0.747          | 32.572              |

*aCorrelation was based multivariate regression analysis.

Figure 2. 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 of about 12.6%.

Figure 3. Spatial distribution of AGB that was derived from a combination of NDFI from SPOT-5 and HV polarization from ALOS PALSAR images. Low biomass intensity occurs mainly in the recently logged areas that appear in grids B3 and C3.

4. 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 NDFI derived from SPOT-5 HRG combined with backscattering coefficient from HV polarization of ALOS
PALSAR gave the best accuracy of estimation. With the $R^2$ of 0.803 and RMSE of 32.572 Mg ha$^{-1}$, the model produced has estimated that study area covering 2,891 ha has a total AGB of 655,390 Mg.

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 the tropical forests.

References
[1] Houghton RA 2005 Tropical deforestation as a source of greenhouse gas emissions. Eds Mutinho and Schwartzman, Tropical deforestation and climate change Belém, Brazil
[2] Gibbs HK, Brown S, O’Niles J, and Foley JA Env Research Letter 2 13
[3] IPCC 2007 Climate Change 2007 Cambridge and New York: Cambridge University Press.
[4] Angelsen A, Brown S, Loisel C, Peskett C, Streck C. and Zarin D. 2009. Reducing emission from deforestation and degradation (REDD): An options assessment report. Meridian Institute 100
[5] Goetz SJ, Baccini A, Laporte NT, Johns T, Walker W, Kellndorfer J, Houghton RA and Sun M 2009 Carbon Bal Mgmt 4(2) 7
[6] Lu D 2006 Int J Rem Sens 27 1297–1328
[7] Asner, GP 2001 Int J Rem Sens 22 3855–62
[8] Sarker LR and Nichol JE 2011 Rem Sens Env 115 968-77
[9] Foody GM, Boyd DS and Cutler ME 2003 Rem Sens Env 85 463-74
[10] Steininger MK 2000 Int J Rem Sens 21 1139-1157
[11] Imhoff ML 1995 IEEE Trans Geosci Rem Sens 33 341–52
[12] Wolter PT and Townsend, PA 2011 Rem Sens Env 115 671-691
[13] Guo Z. W. Ni and G. Sun 2009 IEEE Int. Geosc. Remote Sensing Symp 4 386-89
[14] Amini J and Sri Sumantyo JT 2009 IEEE Trans Geosci Rem Sens 47(12) 4020-26
[15] Wang C and Qi J 2008 Int J Rem Sens 29 6827-49
[16] Moghaddam M, Dungan JL and Acker S 2002 IEEE Trans Geosci Rem Sens 40 2176-87
[17] Araujo LS, Santos JR, Freitas, CC and Xaud HAM 1999. IGARSS 2762-64
[18] Clark B, Suomalainen J and Pelliikka P. 2010. Canadian J. Rem Sens 36(4): 397 – 411
[19] Shimada M, Isoguchi O, Tadono T and Isono K 2009 IEEE Trans Geosci Rem Sens 3 765-68
[20] Hamdan O, Nur Laila CM, Khalid Aziz H and Mohd Hasmani I 2013 AIP Conf Proc 1528: 76-81
[21] Kato R, Tadaki Y and Ogawa, H 1978 Malayan Nature J. 30 211–24
[22] Lucas R, Armstrong J, Fairfax R, Fesham R et al. 2010 IEEE J. Selected Topics in Applied Earth Observations and Remote Sensing 3(4) 576-593
[23] Hamdan O, Khalid Aziz H and Abd Rahman K 2011 J. Trop For Sci 23(3) 318-27
[24] Robinson C, Saatchi S, Neumann M. and Gillespie T 2013 Remote Sensing 5 1001-23
[25] Monteiro A and Souza Jr. 2012 Remote Monitoring for Forest Management in the Brazilian Amazon (Sustainable Forest Management - Current Research) ed Julio J. Diez (InTech Europe) chapter 4 pp 67-86
[26] Rouse JW, Haas RH, Schell JA, Deering DW 1974 Proceedings of Third Earth Resources Technology Satellite-1 Symposium, Greenbelt: NASA SP-351:310–17
[27] Huete AR 1988 Rem Sens Envi 25 295–309
[28] Jiang Z, Huete AR, Didan K and Miura T. 2008 Rem Sens Envi 112(10) 3833-45
[29] Souza Jr C, Roberts DA and Cochrane MA 2005 Rem Sens Envi. 98 329-43