L-BAND SATURATION LEVEL FOR ABOVEGROUND BIOMASS OF DIPTEROCARP FORESTS IN PENINSULAR MALAYSIA

O Hamdan[1, *] , I Mohd Hasmadi[2], H Khali Aziz[1], K Norizah[2] & MS Helmi Zulhaidi[3]

[1]*Forest Research Institute Malaysia, 52109 Kepong, Selangor Darul Ehsan, Malaysia*
[2]*Faculty of Forestry, Universiti Putra Malaysia, 43400 UPM Serdang, Selangor Darul Ehsan, Malaysia*
[3]*Faculty of Engineering, Universiti Putra Malaysia, 43400 UPM Serdang, Selangor Darul Ehsan, Malaysia*

Received July 2014

HAMDAN O, MOHD HASMADI I, KHALI AZIZ H, NORIZAH K & HELMI ZULHAIDI MS. 2015. L-band saturation level for aboveground biomass of dipterocarp forests in Peninsular Malaysia. This study was carried out in lowland and hill dipterocarp forests over the entire Peninsular Malaysia to determine the saturation level of aboveground biomass (AGB) that can be retrieved using L-band synthetic aperture radar (SAR) data. Mosaics of Phase Array Type L-Band SAR (PALSAR) onboard Japanese Advanced Land Observing Satellite (ALOS) were used. Fine-beam dual PALSAR mosaic in horizontal–horizontal(HH) and horizontal–vertical (HV) polarisations with spatial resolution of 25 m were acquired for year 2010. A total of 284 sample plots of AGB were measured on the ground in 2011 and 2012. Pixel-based regression was performed by correlating the AGB of sample plots with the corresponding backscatter on PALSAR data. AGB was estimated on 4.7 mil ha of forests. The backscatter on HV polarisation gave better estimation than HH. The HV backscatter showed good relationship with AGB at < 200 Mg ha^{-1} and tended to saturate at 200 Mg ha^{-1}. About 1.65 billion Mg of AGB was found intact in the study area. The AGB ranged from 21 to 578 Mg ha^{-1} with average of 342 Mg ha^{-1}. A spatially distributed map of AGB was produced.

Keywords: ALOS PALSAR, polarisation, backscatter, limitation, lowland and hill forests

INTRODUCTION

Tropical forest biomass is one of the crucial elements in addressing issues on climate change with regard to carbon cycle. Retrieving forest biomass information for large areas has been challenging due to limited data resource, accessibility, complex forest ecosystem and other technical issues. However, for large area coverage, remote sensing has been proven effective, thus, widely used for forest biomass estimation. Optical and synthetic aperture radar (SAR) systems have potentials in retrieving aboveground biomass (AGB). Both offer specific advantages, challenges and limitations for producing reliable estimate at given scales (Lu 2006). In tropical forests, issues such as cloud cover, complex forest ecosystem and saturation at certain biomass levels remain unanswered and are continually being studied.

In the context of AGB estimation, optical systems have problems in tropical forests (Nichol & Sarker 2011). Spectral reflectance and vegetation indices alone are not reliable indicators of AGB in tropical forests and the direction of their relationship is also inconsistent (Foody et al. 2003). Cloud cover is also one of the critical challenges in the tropics (Asner 2001). SAR, on the other hand, offers a different alternative in estimating AGB. The capability of SAR system to penetrate through the canopy has contributed to advancements in forestry applications. The interest in SAR for monitoring forest cover arises from two advantages: SAR can provide information related to canopy volume and has possibility to acquire data over areas with frequently free cloud cover.

Among the many SAR systems available, L-band has potential for forest AGB estimation as it carries mainly information about larger components of vegetation such as trunks and branches (Imhoff 1995, Wolter & Townsend 2011). Phases Array Type L-Band SAR (PALSAR)

*hamdanomar@frim.gov.my

has been the only satellite-based system (after the Japan Earth Resources Satellite, JERS-1) capable of acquiring data at L-band, which is suitable for forest biomass studies. The L-band backscatter is sensitive and can be related to the growth stage and biophysical parameters of a forest (Le Toan et al. 2004, Shi et al. 2012). Although L-band SAR system offers some advantages in estimating AGB, the saturation problem is common in radar data. It means that the sensitivity of the backscatter will cease at certain level of AGB. This was identified as a critical challenge in the last decade (Lu 2006).

Since PALSAR was operational from 2006 until 2011, many attempts have been made to address the above issues and assess AGB of various forest ecosystems at adequate accuracies. Many studies demonstrate that PALSAR has great potential in estimating vegetation biomass because it can penetrate further into vegetation. A number of AGB retrieval strategies were adopted, ranging from empirical (Lucas et al. 2010, Sandberg et al. 2011) and semi-empirical (Santoro et al. 2009) to more recently numerical models (Burgin et al. 2011). The empirical models have related radar backscatter to AGB using a range of functional forms, including linear (Sandberg et al. 2011), logarithmic and exponential (Englhart et al. 2011, Hamdan et al. 2011) as well as higher degree polynomials (Dobson et al. 1992). Rule-based algorithms adapted to regression problems were also used for the retrieval of bio-geophysical parameters from polarimetric SAR data (Neumann et al. 2012, Sarker et al. 2012). Although agreement of the best models for biomass retrieval has yet to be reached, parametric models are frequently used (Saatchi et al. 2011, Sandberg et al. 2011, Robinson et al. 2013).

However, these studies were conducted in forest ecosystems different from Malaysia. In Malaysia, there are limited studies on applications of PALSAR for estimating biomass (Morel et al. 2011, 2012, Hamdan et al. 2011, 2013, 2014a, 2014b). This indicates that the potential and limitations of PALSAR data in estimating AGB in Malaysia are not fully exploited. This study was conducted with the objectives of (1) determining the saturation level of AGB and (2) investigating the potential application of PALSAR for AGB estimation in dipterocarp forests in Peninsular Malaysia.

MATERIALS AND METHODS

Study area

The dipterocarp forests comprise lowland, hill and upper hill, which are categorised based on land altitude, i.e. < 300, 300–750 and 750–1200 m respectively. The study area comprises lowland and hill dipterocarp forests, occupying about 4.7 million ha or 81% of the total forested land (5.8 million ha) in Peninsular Malaysia. These forests embrace all the well-drained primary forests of the plains, undulating land, and foothills and hilly terrain up to about 750 m altitude. Trees from the family Dipterocarpaceae are dominant species. Almost the entire area is categorised as gazetted reserve forest which is meant for production and protection. About 1.98 million ha have been allocated for protection forests in the form of national parks, wildlife sanctuaries and nature reserves (FDPM 2011). The most common tree species found in this forest come from the genera *Shorea*, *Hopea*, *Dipterocarpus*, *Dryobalanops*, *Neobalacarpus*, *Anisoptera* and *Vatica*. Figure 1 shows the distribution of lowland and hill dipterocarp forests at the study area.

Satellite and supporting data

ALOS PALSAR, an enhanced successor of the JERS-1 SAR was launched from JAXA's Tanegashima Space Center in January 2006. After about 4.5 years of operation, it stopped in April 2011. PALSAR data was in the form of L-band SAR (1270 MHz, 23.62 cm wavelength), dual-polarised mode. The PALSAR images used in this study consisted of a 1 × 1 degree mosaic tiles form a global PALSAR mosaic from 2010 (Shimada & Ohtaki 2010). It was supplied by the Remote Sensing Technology Center of Japan within the framework of the Kyoto and Carbon Initiative. A tile product consists of two bands in horizontal–vertical (HV) and horizontal–horizontal (HH) polarisations at 25 m spatial spacing, geometrically corrected and normalised for topography. It also contained additional ancillary image data layers with information about acquisition dates, local incidence angle and a water- and no-data mask. From this information, it was calculated that at least 53 individual scenes (within 60 km × 60 km) were acquired between May and December 2010, and were used to produce the mosaics of Peninsular Malaysia (Figure 1).

Supporting data was the Landuse Map of Peninsular Malaysia (scale 1: 750,000) over the year 2010. This map was acquired from the Department of Agriculture Peninsular Malaysia. The map was scanned, geometrically corrected and used as a reference layer in classification process. Another supporting data was the digital elevation model acquired from the Shuttle Radar Topography Mission (SRTM). This data were used to classify the forest into specified elevation categories according to forest types.

Forest survey data

A total of 352 sample plots measuring 30 m × 30 m were established in 2011 and 2012. Of the total plots, 284 plots were used for training in modelling process and the remaining 68 plots were reserved for validation process. The forest survey was conducted in a number of field trips that covered mainly the central parts of Peninsular Malaysia. The states included Terengganu, Pahang, Johore, Negeri Sembilan, Selangor, Perak, Kelantan and Perlis. In each plot, all trees with diameter at breast height (dbh) of 5 cm and above were inventoried. Species for every stand was recorded. A plot was divided into four quarters and position (coordinate) was recorded at the centre of the plot using global positioning system. Locations of the sample plots are shown in Figure 1 and a summary of the sample plots is given in Table 1.

The AGB for each plot was calculated based on allometric equation that was developed for lowland dipterocarp forest (Kato et al. 1978).

$$1/H = 1/(2.0 \times D) + 1/61 \quad (1)$$

$$M_s = 0.0313 \times (D^2H) \quad (2)$$

$$M_b = 0.136 \times M_s^{1.070} \quad (3)$$

$$1/M_l = 1/(0.124M_s^{0.794}) + 1/125 \quad (4)$$

where H = total tree height (m), D = dbh (cm), M_s, M_b, and M_l = dry mass of stems, branches and leaves respectively. The AGB of a tree is a

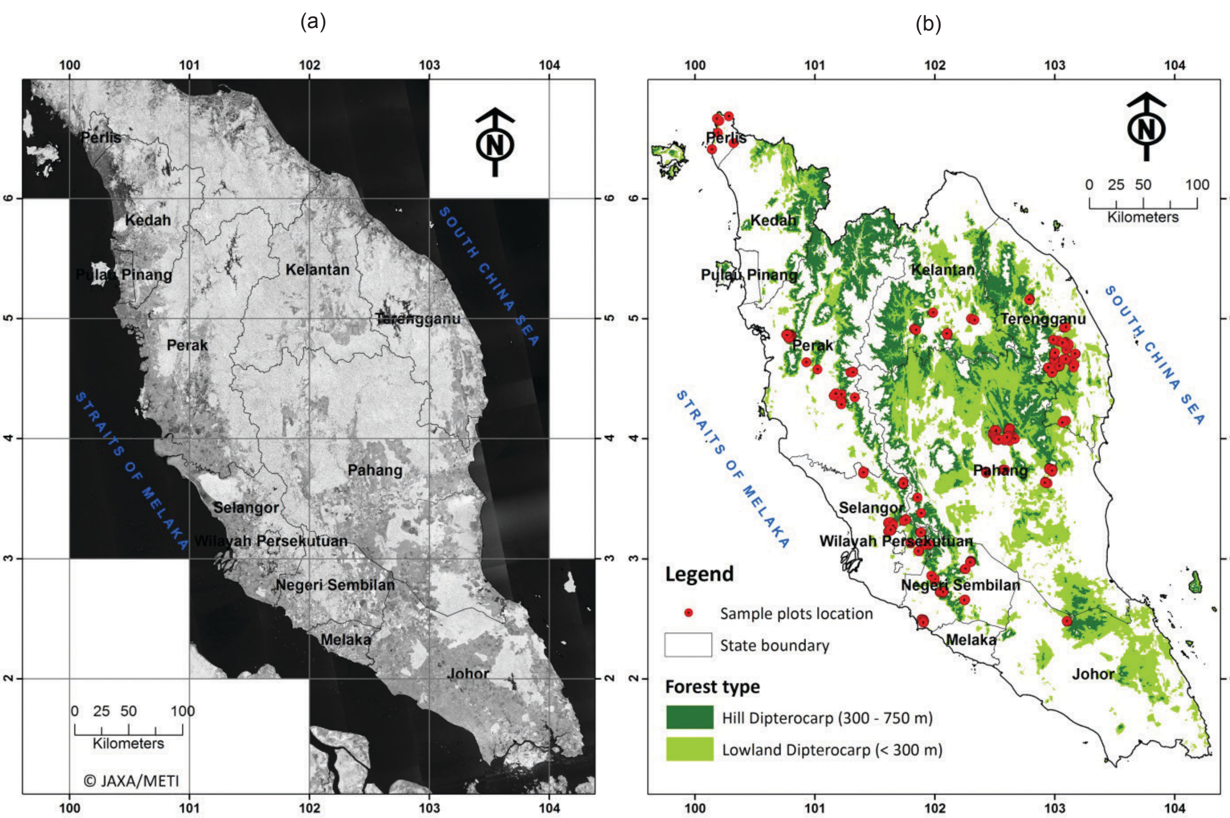

Figure 1 (a) Mosaic of PALSAR images displayed in HV (horizontal–vertical) polarisation and (b) map showing the study area—lowland and hill dipterocarp forests of Peninsular Malaysia

summation of M_s, M_b and M_l calculated based on equations 1–4. It is usually reported in kg per tree. However, it was converted to per hectare basis and reported in Mg ha^{-1} in this paper.

Methodology

This study integrated forest survey data with the PALSAR images. In performing this, sample plots data were gathered and AGB was calculated prior to image analysis. Analysis conducted involved four major steps, namely, (1) image pre-processing, (2) forest–non-forest classification, (3) correlation analysis and (4) validation.

Image pre-processing

The ALOS PALSAR image that was used in this study was built on a 16-bit data type and all pixels had digital numbers (DN) ranging from 0–65,535. These DNs, however, did not represent the radar signal of features or objects on the ground. Therefore, the DN had to be converted to backscatter (i.e. the returned radar signals) known as Normalised Radar Cross-Section (NRCS) and represented in decibel (dB). The equation that was used for the calculation of NRCS for PALSAR was slightly different from other sensors in that the usual sine term had already been included in the DN values. Thus, for the products stored at level 1.5 and above, including mosaic product, the equation for NRSC of any of the polarisation component can be obtained by the following formula with single calibration factor, which can be expressed as equation 5 for distributed scatterers (Shimada et al. 2009).

$$\text{NRCS (dB)} = 10 \times \log_{10} (\text{DN}^2) - 83 \quad (5)$$

Forest–non-forest classification

Forest–non-forest classification was performed on HV polarisation of the images to delineate forests from other landuses. This process is critical to define the boundary of forests and to ensure that the estimated AGB does not include other types of vegetation. The reason is that forests are often confused with rubber, teak and other timber tree plantations, which are common in Peninsular Malaysia and they appear almost identical on both HH and HV polarisation images. To minimise error associated with misclassification, image enhancement was applied to the images. Instead of using only the original backscatter from HH and HV polarisations, an attempt was made to manipulate the backscatter. Polarisation manipulation was done using (1) simple polarisation ratio, (2) polarisation average and (3) polarisation multiplication, as summarised in Table 2. The plantations are normally homogenous and uniform. Therefore, these manipulations were able to separate plantations from natural forests. The boundaries of forests were produced from this process.

The forests were further classified into several forest types using digital elevation model (DEM) acquired from SRTM. The DEM was threshold into two classes,

Table 1 Summary of sample plots

State	No. of plots		Total plots	Total area (ha)
	Lowland dipterocarp	Hill dipterocarp		
Perlis	8	2	10	0.90
Terengganu	56	22	78	7.02
Pahang	57	18	75	6.75
Johore	6	0	6	0.54
Negeri Sembilan	44	14	58	5.22
Selangor	42	32	74	6.66
Perak	23	7	30	2.7
Kelantan	9	12	21	1.89
Total	245	107	352	31.68

which were < 300 m and 300–750 m that represented lowland and hill dipterocarp forests respectively.

Correlation analysis

The backscatter values of PALSAR were extracted from the images, both from the HH and HV polarisations. The AGB values at the sample plots on the ground were correlated with the corresponding backscatter values of HH and HV polarisations using linear regression. This process produced several empirical models that were used to retrieve AGB over the whole study area. The estimation models used AGB as independent variable to observe the sensitivity of the backscatter to the AGB. The relationship between backscatter and AGB is commonly represented in logarithmic function as $y = a \times \ln(x) + b$, where x and y = AGB and image variable respectively, and a and b = model coefficients.

Validation

Similar to the sampling process, validation was also carried out in intervals. A total of 68 validation plots, which contained AGBs ranging from 73.5 to 430.4 Mg ha^{-1} were used to validate the estimates. The root mean square error (RMSE) of each estimation model was calculated based on these validation plots. An absolute accuracy—a measure of the error between the predicted AGB from the PALSAR images and the actual AGB measured on the ground—was calculated for all prediction models. Absolute accuracy is expressed as RMSE:

$$RMSE = \sqrt{\left[\frac{1}{n}\sum_{i=1}^{n}\left((AGB_i - AGB'_i) - \mu\right)^2\right]} \quad (6)$$

where n = the number of validation plots, AGB_i = measured biomass at plot i, AGB'_i = derived/predicted biomass at position i and μ = average of biomass difference.

To further investigate factors contributing to this RMSE, a scatterplot of observed AGB against predicted AGB was produced using the same validation plots.

RESULTS AND DISCUSSION

Summary of forest survey data

In normal practice, trees that have dbhs 10 cm and above are considered for carbon accounting in a forest ecosystem (IPCC 2007). However, certain amount of AGB will be missed if smaller trees are not included, especially when the study area is large (Baccini et al. 2008). Therefore, trees of dbh 5 cm and above were inventoried in this study. It was found that smaller trees (dbh 5.0–9.9 cm) actually occupied only about 3% of the total AGB in a hectare of dipterocarp forests (Table 3). However, trees under this category were plenty in terms of number. Table 3 summarises all measured trees in a total of 31.68 ha of sample plots. Figure 2, on the other hand, shows the relationship between the number of trees and AGB in a hectare of forest. The AGB was actually stored in huge trees with dbh 40 cm and above. Although the number of

Table 2 Image variable used for forest classification

Polarisation manipulation	Description
HV	An image containing pixel values of original backscatter (σ, dB) from HV polarisation
HH	An image containing pixel values of original backscatter (σ, dB) from HH polarisation
HH/HV	Simple ratio generation by dividing HH to HV polarisations (unitless)
HV/HH	Simple ratio generation by dividing HV to HH polarisations (unitless)
(HH + HV)/2	Average of HH and HV (unitless)
√(HH × HV)	Squared root of HH and HV multiplicative product (unitless)

HH = horizontal–horizontal, HV = horizontal–vertical huge trees was low, the amount of AGB within these trees was large.

The forest–non-forest classification

The classification that was carried out over the original HH and HV polarisations and all the manipulations found that PALSAR images had different capabilities in defining forests. The backscatter values generally ranged from -16 to -8 dB and -11 to -4 dB for HV and HH polarisations respectively for dipterocarp forest. The accuracy of classification was checked using similar sample plots as used for AGB sampling. HV polarisation alone defined the forests at 91.8% accuracy, but the classification accuracy

Table 3 Average number of trees and AGB in a hectare of sample plots

Dbh class (cm)	No. of trees (count ha^{-1})	No. of trees (%)	AGB (Mg ha^{-1})	Percentage AGB (%)
5.0–9.9	633	53.6	11.5	3.2
10.0–19.9	314	26.6	43.8	12.2
20.0–29.9	117	9.9	61.3	17.1
30.0–39.9	53	4.5	63.0	17.6
40.0–49.9	34	2.9	75.6	21.1
≥ 50.0	29	2.5	103.0	28.7
Total	1180	100	358.2	100

Dbh = diameter at breast height, AGB = aboveground biomass

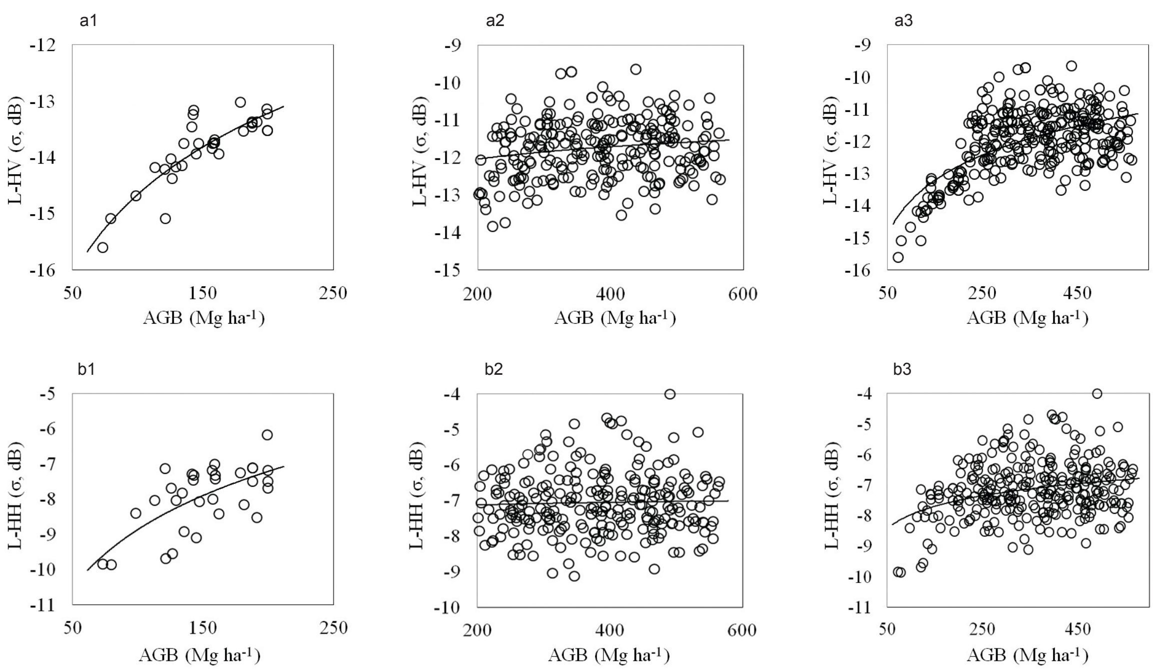

Figure 2 Scatterplots of correlations between backscatter and AGB on (a) HV and (b) HH polarisations; AGB from all sample plots were segregated into intervals (1) < 200 Mg ha^{-1}, (2) > 200 Mg ha^{-1} and (3) overall sample plots; AGB = aboveground biomass, HH = horizontal–horizontal, HV = horizontal–vertical

was improved slightly (at 93.2%) when the √(HH × HV) manipulation was used. While HH polarisation was sensitive to object orientation, HV was more sensitive to object roughness. Therefore, HH interprets plantation areas that have systematic arrangement and homogenous canopies better than HV. HV has very good response towards natural forest canopies that are more complex than plantations. Therefore, a combination of both polarisations was able to delineate forest from other plantations and thus improved the classification accuracy. The study introduced a new image enhancement technique for forest cover classification. Misclassification was spotted at the edges of forest or at the transitional areas between forest and agricultural crops, where pixels were confused by the surrounding landuse classes such as rubber and mature oil palm plantations. It was found that HH polarisation alone as well as other manipulations did not perform well at delineating forests from other features. The results indicates that the L-band PALSAR data is a good system to be utilised for large-area mapping of dipterocarp forests. The only reason is that the L-band backscatter is strong when it interacts with canopies of dipterocarp forests. The classification results combined with the DEM from SRTM had been used for delineating lowland and hill dipterocarp forests. The study found these forests occupied about 4.7 mil ha in Peninsular Malaysia as summarised in Table 4.

Aboveground biomass estimation

Table 5 lists all empirical models that have been generated from regressions. Correlations between AGB and backscatter in HV and HH polarisations were constructed separately. In addition, the AGB from sample plots was separated into two intervals, < 200 and ≥ 200 Mg ha^{-1}. An overall scatterplot was also generated to observe the overall response of backscatter to the AGB. Figure 2 shows the scatterplots of these correlations.

Based on the correlations, the backscatter of HV polarisation gave better r^2 compared with the HH. The HV backscatter ranged from -16 to -10 dB and the saturation point concentrated within the range -13 to -11 dB (Figure 2). Rapid increment could be seen especially at lower biomass level (i.e. up to 200 Mg ha^{-1}) and decreased towards higher AGB. The trend line became almost constant at about -12 dB when the AGB exceeded 200 Mg ha^{-1}. The errors associated with estimation models are represented by residual errors which measure the deviation of AGB values from the best-fit line (Table 5). Errors were larger at AGB > 200 Mg ha^{-1}. The

Table 4 Extents of lowland and hill dipterocarp forests in the study area

Forest type	Lowland dipterocarp forest (ha)	Hill dipterocarp forest (ha)	Total (ha)
Extent (ha)	2,704,815.54	2,004,990.80	4,709,806.34
Percentage (%)	57.43	42.57	100

Table 5 Correlation functions and r^2 of HV and HV backscatter against AGB intervals

Polarisation	AGB interval (Mg ha^{-1})	No. of sample plots (n)	Model coefficient		r^2	Residual error (± Mg ha^{-1})
			a	b		
HV	< 200	32	2.0847	- 24.261	0.7558	18.89
	> 200	252	0.4750	- 14.558	0.0264	89.82
	Overall	284	1.5326	- 20.890	0.3553	97.66
HH	< 200	32	2.3828	- 19.840	0.4335	26.71
	> 200	252	0.1096	- 7.7060	0.0011	98.42
	Overall	284	0.6757	- 11.083	0.0834	118.10

AGB = aboveground biomass, HV = horizontal–vertical, HH = horizontal–horizontal results were even worse for HH polarisation. The results thus confirmed that saturation occurred at this level.

It has been reported that at a given polarisation and incidence angle, the saturated backscatter value for forest was within a small range of backscatter, typically between -8 and -11 dB at HH and between -11 and -15 dB at HV (Le Toan et al. 2004). The dynamic range was primarily determined by the backscatter at low levels of AGB. It increased with decreasing frequency and was higher at HV compared with HH polarisation. The increase in backscatter with effective vegetation water content led to differences in the saturation level as a function of AGB and/or the degree of scatter observed in the relationship with AGB.

Saturation levels vary with the type and structure of forests. Previous studies reported that saturation occurred in AGB ranges of 80 to 150 Mg ha^{-1} for savanna forest (Lucas et al. 2010), 40 to 150 Mg ha^{-1} for boreal and temperate forests (Le Toan et al. 1992, Sandberg et al. 2011), 97 and 270 Mg ha^{-1} for HH and HV polarisation respectively for dense forest, 40 to 150 Mg ha^{-1} in the tropics (Hamdan et al. 2011, Saatchi et al. 2011) and 150 Mg ha^{-1} for mangrove forest (Hamdan et al. 2014a). Accuracy is mostly influenced by tree density, tree size, soil surface roughness, soil moisture and the layering effect of the SAR itself (Quinones & Hoekman 2004). Factors such as orientation of trees, polarimetry, incidence angle and crown structure also play an important role in biomass estimation (Watanabe et al. 2006, Guo et al. 2009). Tree height was the prominent factor that affected backscattering. Nevertheless, variations in floristic composition, forest structure and management practices can have important effect on the results (Narvaes et al. 2007). These were consistent with findings observed in the study. However, the saturation level was slightly higher due to the allometric equation that was used for estimating AGB. The empirical model generated from overall sample plots in HV polarisation was applied to estimate AGB in the entire study area. The model converted the pixel values into AGB in the unit of Mg ha^{-1}. Figure 3 shows the spatial distribution of AGB in the study area. From the map, total AGB in about 4.7 million ha of the study area was estimated at 1,650,819,055 Mg. Table 6 summarises the variation of AGB over the study area. Figure 4 shows the distribution of AGB in the study area, represented by histogram of frequency of pixel occurrences. Surprisingly, the distribution was normal for the AGB throughout the study area. Further classification was made to the AGB distribution, reported in intervals as shown in Figure 5. More than half of the study area comprised AGB within the range of 300–400 Mg ha^{-1}.

The AGB estimated in this study was in agreement with many other biomass studies in Malaysian forests. Brown et al. (1989) showed that the highest AGB for primary moist forest was in Malaysia (255–446 Mg ha^{-1}), followed by Cameroon (238–314 Mg ha^{-1}), French Guiana (280–283 Mg ha^{-1}) and Sri Lanka (153–221 Mg ha^{-1}). FAO (1973) reported that biomass for mixed dipterocarp forest was 280–330 Mg ha^{-1} in Sarawak and 650 Mg ha^{-1} in Gunung Mulu (Proctor et al. 1983). A study found that the AGB of lowland dipterocarp forest at 10 different locations in Peninsular Malaysia ranged from 300 to 570 Mg ha^{-1} with an average of 430 Mg ha^{-1} (Hikmat 2005).

Validation of the estimates

It was found that the RMSE for the predictions varied along with the intervals as summarised in Table 7. The smallest RMSE was observed at 19.32 Mg ha^{-1} when AGB was < 200 Mg ha^{-1} and increased considerably to 79.58 Mg ha^{-1} when AGB exceeded 200 Mg ha^{-1}. Overall the RMSE was about the summation of both intervals (98.76 Mg ha^{-1}) when all validation plots were included. The propagation of errors was found to be significantly higher at AGB > 200 Mg ha^{-1} and became larger as the amount of biomass increased (Figure 6). Taking into consideration the average estimation error from all the validation plots, the predicted AGB was underestimated by about 15% compared with the measured AGB on the ground. This is indicated by the best-fit line, which is lying under the perfect agreement (dashed line) between the predicted and the measured AGB.

CONCLUSIONS

The study has successfully quantified the AGB on lowland and hill dipterocarp forests in Peninsular Malaysia. The extents of forest cover were defined accurately by the L-band

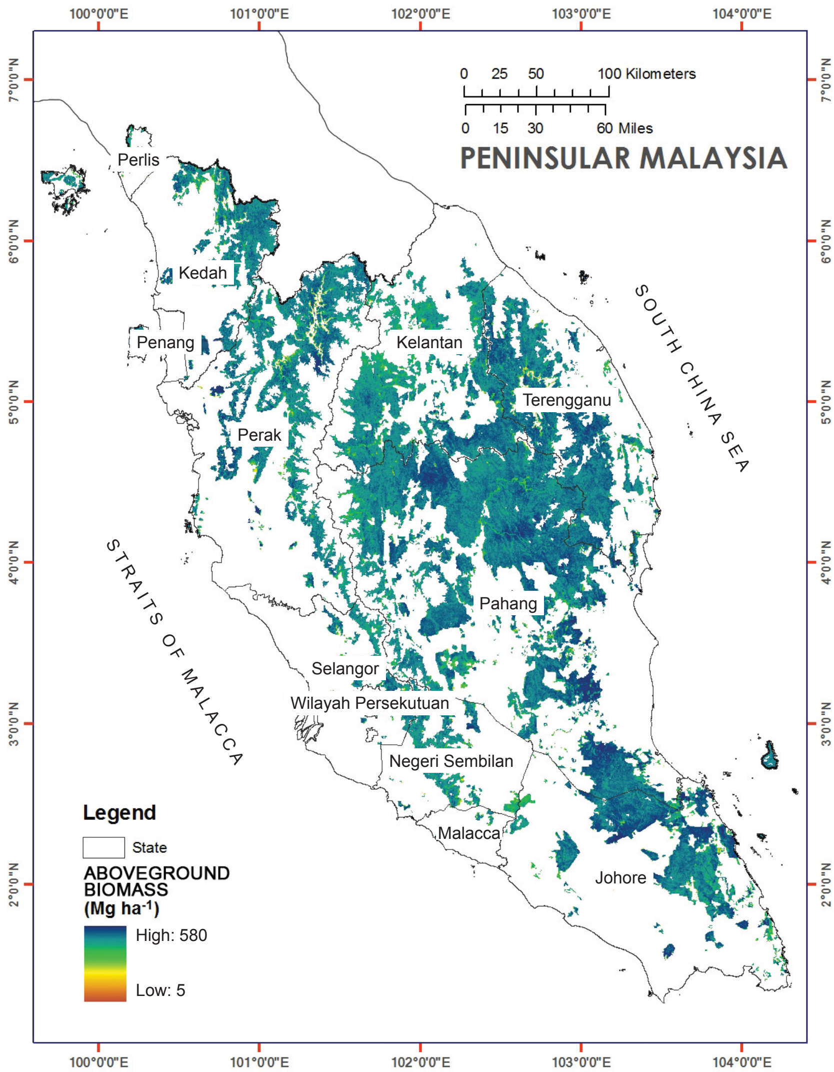

Figure 3 Spatial distribution map of aboveground biomass for the study area

Table 6 Estimated aboveground biomass in the study area in 2010

Parameter	Aboveground biomass ($Mg\ ha^{-1}$)
Minimum	21.02
Maximum	578.01
Mean	342.01
Mode	341.57
Standard deviation	73.07

PALSAR data. Total AGB in 2010 was estimated at 1.65 billion Mg. The study confirmed that the HV backscatter started to saturate at AGB of 200 $Mg\ ha^{-1}$. This was identified as a major limitation of the study. A direct approach may not be appropriate to address this limitation and some indirect approaches are needed to produce accurate estimate of very high levels of biomass. Nevertheless, the study provided an alternative for AGB retrieval that could be utilised in a practical manner to assist in the management and protection of forested areas.

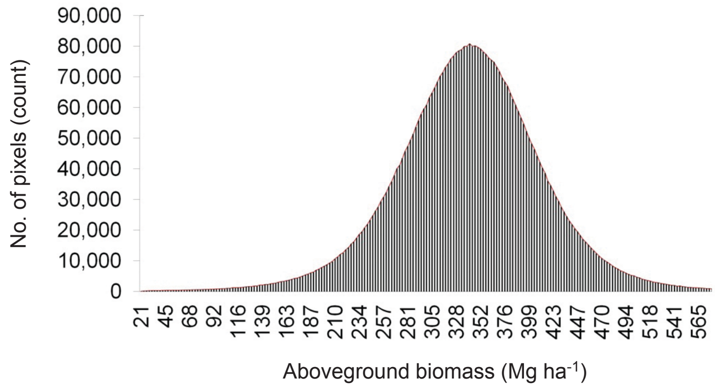

Figure 4 Histogram of aboveground distribution over the study area

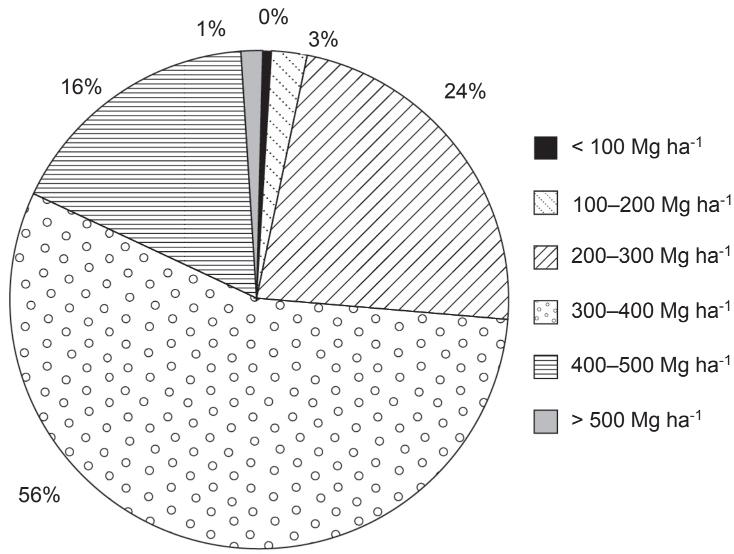

Figure 5 Composition of aboveground biomass divided into several intervals

The study also provided further recognition of the expanding capacity of space-based remote sensing to meet the requirements of large-area forest mapping and monitoring activities at the national scale. The approach described can be used as a practical guide for countries for preliminary design of national level biomass assessments.

ACKNOWLEDGEMENTS

This work was undertaken within the framework of the JAXA Kyoto and Carbon Initiative (Phase 3). ALOS PALSAR data were provided by JAXA EORC. M Shimada (JAXA) is particularly thanked for provision of the dataset through RESTEC. Financial support to conduct the forest survey was provided by the Forest Research Institute Malaysia (FRIM) through the 10^{th} Malaysian Plan development allocation. Special gratitude to the State Forestry Departments of Terengganu, Pahang, Johore, Negeri Sembilan, Selangor, Perak, Kelantan and Perlis for providing ancillary data and access to some of the forest reserves. Thanks to all staff from the Geoinformation Programme, FRIM for assistance during the forest survey.

REFERENCES

Asner GP. 2001. Cloud cover in Landsat observations of the Brazilian Amazon. *International Journal of Remote Sensing* 22: 3855–3862.

Baccini A, Laporte N, Goetz SJ, Sun M & Dong H. 2008. A first map of tropical Africa's above-ground biomass derived from satellite imagery. *Environmental Research Letter* 3: 1–9.

Brown S, Gillespie AJR & Lugo AE. 1989. Biomass estimation methods for tropical forests with applications to forest inventory data. *Forest Science* 35: 88–902.

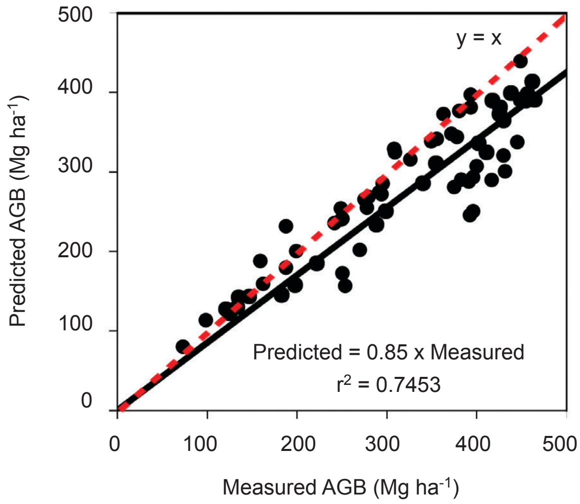

Figure 6 Propagation of errors of aboveground biomass (AGB) in the study area

Table 7 Root mean square error (RMSE) calculated from the validation process

AGB interval (Mg ha^{-1})	No. of validation plots	RMSE (± Mg ha^{-1})
< 200	22	19.32
> 200	46	79.58
Overall	68	98.76

AGB = aboveground biomass

Burgin M, Clewley D, Lucas R & Moghaddam M. 2011. A generalized radar backscattering model based on wave theory for multilayer multispecies vegetation. *IEEE Transactions on Geoscience and Remote Sensing* 49: 4832–4845.

Dobson MC, Ulaby FT, Le Toan T et al. 1992. Dependence of radar backscatter on coniferous forest biomass. *IEEE Transaction on Geoscience and Remote Sensing* 30: 412–415.

Englhart S, Keuck V & Siegert F. 2011. Aboveground biomass retrieval in tropical forests—the potential of combined X- and L-band SAR data use. *Remote Sensing of Environment* 115: 1260–1271.

FAO (Food and Agriculture Organization). 1973. *The Timber Species of the Mixed Dipterocarp Forests of Sarawak and Their Distribution*. FAO Working Paper 21. FAO, Rome.

FDPM (Forestry Department Peninsular Malaysia). 2011. *Annual Report 2010*. Forestry Department Peninsular Malaysia, Kuala Lumpur.

Foody GM, Boyd DS & Cutler ME. 2003. Predictive relations of tropical forest biomass from Landsat TM data and their transferability between regions. *Remote Sensing of Environment* 85: 463–474.

Guo Z, Ni W & Sun G. 2009. Analysis of the effect of crown structure changes on backscattering coefficient using modelling and SAR data. *IEEE Transactions on Geoscience and Remote Sensing* 4: 386–389.

Hamdan O, Khali Aziz H & Abd Rahman K. 2011. Remotely sensed L-Band SAR data for tropical forest biomass estimation. *Journal of Tropical Forest Science* 23: 318–327.

Hamdan O, Khali Aziz H & Mohd Hasmadi I. 2014a. L-band ALOS PALSAR for biomass estimation of Matang Mangroves, Malaysia. *Remote Sensing of Environment* 155: 69–78.

Hamdan O, Mohd Hasmadi I, Khali Aziz H, Norizah K & Helmi Zulhaidi MS. 2014b. Factors affecting L-band ALOS PALSAR backscatter on tropical forest biomass. *Global Journal of Science Frontier Research* 14: 51–63.

Hamdan O, Nur Laila CM, Khali Aziz H & Mohd Hasmadi I. 2013. L-Band Synthetic Aperture Radar (SAR) response to the tropical forest stands for carbon stock assessment. *American Institute of Physics Conference Proceedings* 1528: 76–81.

Hikmat A. 2005. Biomass estimation, carbon storage and energy content of three virgin jungle reserves in Peninsular Malaysia. *Media Konservasi* 5: 1–8.

Imhoff ML. 1995. A theoretical analysis of the effect of forest structure on synthetic aperture radar backscatter and the remote sensing of biomass. *IEEE Transactions on Geoscience and Remote Sensing* 33: 341–352.

IPCC (Intergovernmental Panel and Climate Change). 2007. *Climate Change 2007: Synthesis Report*. Contribution of Working Group I, II and III to the

Fourth Assessment Report of the Intergovernmental Panel on Climate Change. IPCC, Geneva.

Kato R, Tadaki Y & Ogawa H. 1978. Plant biomass and growth increment studies in Pasoh forest. *Malayan Nature Journal* 30: 211–224.

Le Toan T, Beaudoin A, Riom J & Guyon D. 1992. Relating forest biomass to SAR data. *IEEE Transaction on Geosciences and Remote Sensing* 30: 403–411.

Le Toan T, Quegan S, Woodward I, Lomas M, Delbart N & Picard C. 2004. Relating radar remote sensing of biomass to modeling of forest carbon budgets. *Climate Change* 76: 379–402.

Lu D. 2006. The potential and challenge of remote sensing-based biomass estimation. *International Journal of Remote Sensing* 27: 1297–1328.

Lucas R, Armston J, Fairfax R et al. 2010. An evaluation of the PALSAR L-band backscatter—aboveground biomass relationship Queensland, Australia: impacts of surface moisture condition and vegetation structure. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 3: 576–593.

Morel AC, Fisher JB & Malhi Y. 2012. Evaluating the potential to monitor aboveground biomass in forest and oil palm in Sabah, Malaysia, for 2000–2008 with Landsat ETM+ and ALOS-PALSAR. *International Journal of Remote Sensing* 33: 3614–3639.

Morel AC, Saatchi SS, Malhi Y et al. 2011. Estimating aboveground biomass in forest and oil palm plantation in Sabah, Malaysian Borneo using ALOS PALSAR data. *Forest Ecology and Management* 262: 1786–1798.

Narvaes IS, Queiroz AS & Santos JR. 2007. Evaluation of the interaction between SAR L-band signal and structural parameters of forest cover. *IEEE Transactions on Geoscience and Remote Sensing* 42: 1607–1610.

Neumann M, Saatchi SS, Ulander LMH & Fransson JES. 2012. Assessing performance of L- and P-band polarimetric interferometric SAR data in estimating boreal forest above-ground biomass. *IEEE Transactions on Geoscience and Remote Sensing* 50: 714–726.

Nichol JE & Sarker MLR. 2011. Improved biomass estimation using the texture parameters of two high-resolution optical sensors. *IEEE Transaction on Geosciences and Remote Sensing* 49: 930–948.

Proctor J, Anderson JM, Chai P & Vallack HW. 1983. Ecological studies in four contrasting rain forest in Gunung Mulu National Park, Sarawak. *Journal of Ecology* 71: 237–260.

Quinones MJ & Hoekman DH. 2004. Exploration of factors limiting biomass estimation by polarimetric radar in tropical forests. *IEEE Transaction on Geosciences and Remote Sensing* 42: 86–104.

Robinson C, Saatchi S, Neumann M. & Gillespie T. 2013. Impacts of spatial variability on aboveground biomass estimation from L-band radar in a temperate forest. *Remote Sensing* 5: 1001–1023.

Saatchi SS, Marlier M, Chazdon RL, Clark DB & Russell AE. 2011. Impact of spatial variability of tropical forest structure on radar estimation of aboveground biomass. *Remote Sensing of Environment* 115: 2836–2849.

Sandberg G, Ulander LMH, Fransson JES, Holmgren J & Le Toan T. 2011. Land P-band backscatter intensity for biomass retrieval in hemiboreal forest. *Remote Sensing of Environment* 115: 2874–2886.

Santoro M, Fransson JES, Eriksson LEB, Magnusson M, Ulander LMH & Olsson H. 2009. Signatures of ALOS PALSAR L-band backscatter in Swedish forest. *IEEE Transaction on Geoscience and Remote Sensing* 47: 4011–4019.

Sarker MLR, Janet N, Baharin A, Busu I & Alias AR. 2012. Potential of texture measurements of two-date dual polarisation PALSAR data for the improvement of forest biomass estimation. *ISPRS Journal of Photogrammetry and Remote Sensing* 69: 146–166.

Shi JC, Du Y, Du JY et al. 2012. Progresses on microwave remote sensing of land surface parameters. *Science China Earth Science* 55: 1052–1078.

Shimada M, Isoguchi O, Tadono T & Isono K. 2009. PLASAR radiometric calibration and geometric calibration. *IEEE Transaction on Geosciences and Remote Sensing* 3: 765–768.

Shimada M & Ohtaki T. 2010. Generating large-scale high-quality SAR mosaic datasets: application to PALSAR data for global monitoring. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 3: 637–656.

Watanabe M, Shimada M, Rosenqvist A et al. 2006. Forest structure dependency of the relation between L-band σ^o and biophysical parameters. *IEEE Transactions on Geoscience and Remote Sensing* 44: 3154–3165.

Wolter PT & Townsend PA. 2011. Estimating forest species composition using a multi-sensor fusion approach. *Remote Sensing of Environment* 115: 671–691.

