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Estimating aboveground biomass in forest and oil palm plantation in Sabah, Malaysian Borneo using ALOS PALSAR data

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ABSTRACT

Conversion of tropical forests to oil palm plantations in Malaysia and Indonesia has resulted in large-scale environmental degradation, loss of biodiversity and significant carbon emissions. For both countries to participate in the United Nation's REDD (Reduced Emission from Deforestation and Degradation) mechanism, assessment of forest carbon stocks, including the estimated loss in carbon from conversion to plantation, is needed. In this study, we use a combination of field and remote sensing data to quantify both the magnitude and the geographical distribution of carbon stock in forests and timber plantations, in Sabah, Malaysia, which has been the site of significant expansion of oil palm cultivation over the last two decades. Forest structure data from 129 ha of research and inventory plots were used at different spatial scales to discriminate forest biomass across degradation levels. Field data was integrated with ALOS PALSAR (Advanced Land-Observing Satellite Phased Array L-band Synthetic Aperture Radar) imagery to both discriminate oil palm plantation from forest stands, with an accuracy of 97.0% ($\kappa = 0.64$) and predict AGB using regression analysis of HV-polarized PALSAR data ($R^2 = 0.63$, $p < .001$). Direct estimation of AGB from simple regression models was sensitive to both environmental conditions and forest structure. Precipitation effect on the backscatter data changed the HV prediction of AGB significantly ($R^2 = 0.21$, $p < .001$), and scattering from large leaves of mature palm trees significantly impeded the use of a single HV-based model for predicting AGB in palm oil plantations. Multi-temporal SAR data and algorithms based on forest types are suggested to improve the ability of a sensor similar to ALOS PALSAR for accurately mapping and monitoring forest biomass, now that the ALOS PALSAR sensor is no longer operational.

1. Introduction

Conversion of secondary forest to oil palm plantation is a huge concern for carbon emissions and biodiversity conservation in Southeast Asia. The forests in this region are a large carbon reserve, having among the highest carbon densities of all undisturbed tropical forests (Slik et al., 2010); however, aggressive timber extraction over the past several decades has severely decreased this carbon store (Houghton, 2005). Borneo has suffered among the highest levels of logging in Southeast Asia with extraction rates of greater than 100 m^3 ha^{-1} (Collins et al., 1991; Sundberg, 1983), with 80% of its lowlands already degraded by selective logging (Curran and Trigg, 2006). Pressure on these forest reserves will continue to increase as volumes of readily harvestable timber dwindle, sometimes resulting in the conversion of these areas to oil palm plantations. As very little if any unprotected "primary forest" in this region remains and only previously logged areas can be cited for conversion, the focus of this study has been to compare AGB of logged and degraded forest with AGB of oil palm plantation.

Abbreviations: AGB, aboveground biomass; ALOS-PALSAR, Advanced Land-Observing Satellite Phased Array L-band Synthetic Aperture Radar; AMSR-E, Advanced Microwave Scanning Radiometer – Earth Observing System; DBH, diameter at breast height; FBD, fine beam dual-polarization; FRC, [Sabah] Forest Research Centre; FSC, Forest Stewardship Council; GPS, global positioning system; JERS-1, Japanese Earth Resources Satellite 1; MLC, maximum likelihood classification; RMSE, root mean square error; SAR, synthetic aperture radar; SSSB, Sabah Softwoods Sendirian Berhad.

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Past efforts at estimating the degree of forest loss due to expansion of oil palm plantation, such as that by Koh and Wilcove (2008), have used data from the United Nations Food and Agriculture's (FAO) Forest Resource Assessment (FRA). These data allowed them to estimate the amount of planted oil palm area replacing natural forest in Malaysia and Indonesia. However, this analysis was not able to differentiate the aboveground biomass (AGB) stored in this forest before clearance and therefore could not estimate the carbon emissions due to this land conversion. As a result of studies like these, concerted efforts are underway to improve the mapping of AGB using remote sensing.

This study focuses on Sabah, Malaysian Borneo, which covers 73,731 km^2 or 10% of Borneo's total area. It is also the Malaysian state with the largest area of planted oil palm, covering approximately 17% of the state's total land area (MPOB, 2008). Under the Malaysian National Forest Policy 45% of Sabah's land area is designated as Permanent Forest Reserve, which are unlikely to be converted to oil palm; although they will continue to be logged. Berry et al. (2008) predicted that by the end of 2010 all of the remaining natural forest outside of protected areas will have been logged at least once. Better AGB estimates could be pivotal for prioritizing areas needing enhanced protection and/or identifying areas being degraded unsustainably.

1.1. Mapping aboveground biomass

Estimating the carbon implications of this forest degradation and large-scale conversion is still relatively uncertain considering the errors in regional carbon stock estimates. While carbon is stored in both vegetation and soil, 89% of carbon losses are due to loss of living biomass (Houghton, 2005); therefore, efforts have been focused on estimating AGB of vegetation at the landscape scale (Saatchi et al., 2007b). Mapping AGB using remote sensing has been a significant challenge to researchers, but is extremely important for future implementation of carbon credit verification in the Land-use Change and Forestry (LUCF) sector (GOFC-GOLD, 2009).

Mapping AGB in tropical regions can be especially challenging due to the complex canopy structure as well as predominant cloud cover. Passive optical data can only sense the canopy in two dimensions making it unable to sense the sub-canopy structure, including canopy height (Almeida-Filho et al., 2007; Anaya et al., 2009; Olander et al., 2008). Therefore, passive optical data has been considered to have limited use for estimating AGB in comparison to synthetic aperture radar (SAR) and light detection and ranging (LiDAR) data, which are sensitive to the forest structure (Drake et al., 2003; Gibbs et al., 2007; Le Toan et al., 2004; Patenaude et al., 2005). SAR data has been effective in directly estimating forest AGB in African (Mitchard et al., 2009), Latin American (Saatchi et al., in press) and more recently in Southeast Asian forests, namely in peatland areas of Kalimantan (Englhart et al., 2011). Also, efforts have attempted to relate height variables (e.g. canopy height and lorey's height) to AGB estimates to be applicable for techniques able to estimate forest height directly from remote sensing data (Köhler and Huth, 2010; Saatchi et al., 2011).

1.2. Synthetic aperture radar

SAR data acquisition entails emission of a microwave of discrete wavelength, 1–150 cm, which interacts with the earth's surface described by a scattering coefficient, σ^0. This coefficient is a dimensionless value, which is mapped as intensity using a logarithmic scale in decibels [dB] (Waring et al., 1995). Each pixel of a SAR image is a combination of several backscattering coefficients, which can lead to either constructive or deconstructive interference creating a speckle effect in an image (Balzter, 2001). Smoothing this speckle through kernel filters or reducing the resolution of SAR backscatter to 50 or 100 m improves the quality of intensity information (Le Toan et al., 2004; Saatchi et al., in press). Finally, more advanced SAR sensors discriminate returning signals by polarization, providing information on the structure of the backscattering surface. With polarimetric SAR, the backscatter signal from the surface is measured in a combination of horizontal (H), transmitted or received parallel to the ground surface, and vertical, (V) transmitted or received perpendicular to the surface, polarizations.

Before the launch of the Advanced Land-Observing Satellite (ALOS), it was not considered possible to generate biomass maps from the radar sensors available (e.g. JERS-1, ERS, etc.). The Japanese Earth Resources Satellite 1 (JERS-1), launched from 1992 to 1998, has been used in conjunction with optical sensors to aid in deforestation monitoring; however the use of only one polarization (HH) severely limited its ability to differentiate between disturbance types. The longer wavelength of the L-band is particularly sensitive to the primary, secondary branches and stems of forests, although it also exhibits saturation to dense forest (Quegan and Le Toan, 2002). ALOS launched in 2006 with the L-band (wavelength: ~24 cm) synthetic aperture radar sensor, PALSAR, onboard was hailed as a significant contribution to the field of forest monitoring (Rosenqvist, 2003), namely for biomass estimation and/or growing stock volume (Eriksson et al., 2003). Unfortunately, the PALSAR sensor failed on May 12, 2011; therefore, new imagery will not be available for future monitoring efforts.

ALOS-PALSAR acquired L-band data in five different modes; however, this study used fine beam dual polarization (FBD) data HH and HV. Dual and quad band polarizations increase the sensitivity of the signal in order to overcome saturation for biomass values greater than 50 Mg ha^{-1} (Quegan and Le Toan, 2002). Nevertheless, PALSAR FBD may not be an effective dataset for mapping very biomass-rich forest types due to saturation of the signal (Gibbs et al., 2007; Magnusson et al., 2008) or its inability to distinguish between types of severely degraded forests (Watanbe et al., 2007).

For this study it was considered necessary to explore the range of AGB values by forest disturbance type and oil palm age in order to reliably estimate changes in AGB from forest to oil palm plantation. Also, to map AGB in these two structurally different land-cover types a reliable means of differentiating their respective areas was needed. Therefore, the main aims of this paper are: (1) present mean carbon stock values for different land-cover types across Sabah (2) investigate the potential for ALOS-PALSAR data to differentiate oil palm plantation from forest area and (3) assess generated logarithmic relationships between AGB and SAR backscatter for estimating biomass across Sabah.

2. Materials and methods

2.1. Study area

The study sites sampled were located in six forest reserves and three oil palm plantations across much of eastern, lowland Sabah. Annual precipitation ranges from 2000 to 3000 mm due to the influence of two monsoons acting in November–March and a drier one in June–July, creating relative dry seasons in April–May and August–September (Marsh and Greer, 1992). Temperatures are typical for a moist, tropical climate, and in the lowlands rarely go below 20 °C or above 30 °C, with means of 26.7–27.7 °C. The lowland forest is dominated by the Dipterocarpaceae family, with over 180 species of this family in Sabah alone (Whitmore, 1984). The forest area sampled ranged from mixed Dipterocarp forest, both protected and logged, heath forest (a.k.a. *kerangas*) and some areas

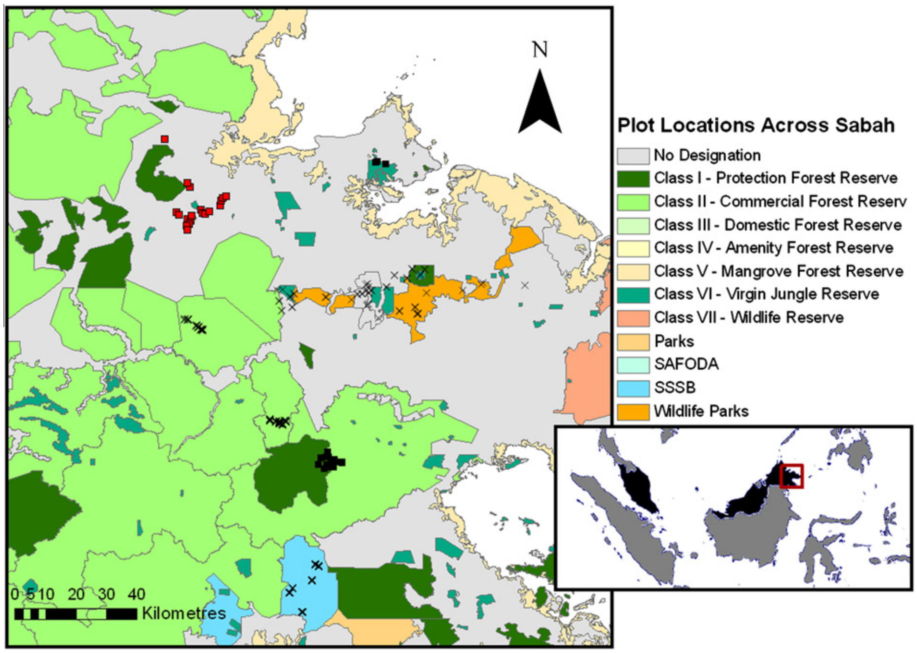

Fig. 1. Forest reserve types for Sabah, Malaysian Borneo. Depicts location of sampled forest and plantation plots. Black crosses indicate transects, black squares indicate square forest plots and red squares designate oil palm plantations sampled for this study (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

of peat swamp forest (see Fig. 1). Ninety-five percent of the study area was below 600 meters elevation and with slopes less than 18°, both of which are cut off values for areas suitable for oil palm cultivation.

The forest reserves sampled were Deramakot, Danum Valley, Malua, Ulu Segama and the lower Kinabatangan flood plain. Deramakot Forest Reserve is a mixed Dipterocarp forest, managed by the Sabah Forestry Research Centre (FRC), which covers an area greater than 55,000 with 51,000 ha currently logged under Forestry Stewardship Council (FSC) guidelines. Danum Valley consists of 43,800 ha of relatively undisturbed, lowland Dipterocarp forest managed by Yayasan Sabah. Bordering Danum Valley are the forest reserves Ulu Segama and Malua, which combined cover 236,825 ha of logged Dipterocarp forest. Several forest reserves along the lower Kinabatangan flood plain were sampled by the FRC and WWF-Malaysia as part of the Kinabatangan Landscape Conservation Initiative Project. The whole area was once over 330,000 ha of intact forest; however, over the last several decades approximately 68% of this region has been degraded through human activities (WWF-Malaysia, 2007). Transects for this study were stratified across mixed Dipterocarp forest, freshwater swamp forest and peatswamp forest. Timber plantations were sampled from the Sabah Softwoods Sendirian Berhad (SSSB) site, 70 km north of Tawau, consisting of two species, *Acacia mangium* and *Albizia ferrucania*. Oil palm plantations, *Elaeis guineensis*, were sampled from Wilmar International Limited's (formerly Perlis Plantations Berhad, PPB) Sapi plantations located near Sandakan.

2.2. Ground data

Twenty-two hectares of forest mensuration data were collected between April and November 2008, along 0.5- (20 by 250 m), 1.0- (20 by 500 m) and 1.5-ha (20 by 750 m) line transects stratified across logging intensities and years since logging. Data collected included (i) diameter at breast height (DBH) measurements for all trees with DBH 10 cm or greater, (ii) height measurements for a subset of trees and (iii) species of all trees in order to estimate their wood density. Average wood density values for each species or genus were compiled from Brown (1997) and the World Agroforestry Center's Wood Density Database (ICRAF, 2008). Three hectares of line transects in timber plantation were collected as well as 5 ha of 0.25-ha plots in oil palm plantation, stratified by years since planting. Demarcations were made every 10 m, in order to monitor variation along transects. To augment this data set, we compiled existing datasets of vegetation biomass in the region, 74 ha of similar line transects collected along the Kinabatangan River (WWF-Malaysia, 2007), 30 square 1-ha plots in logged and unlogged forest (Berry et al., 2008) and three square 1-ha plots in primary forest over three different soil types (Banin, 2010). Often remaining forest areas are located in hilly areas, unsuitable for agricultural cultivation. This could make forest mensuration data collection along line transects challenging as well as relating estimated AGB values to SAR backscatter. Efforts to reduce these errors will be discussed in the next section.

A number of mensuration variables were generated from these field data in order to compare with satellite images acquired over the same time period; however only average height, dominant height and six different biomass estimates are presented. Analysis of these variables was performed across a number of plot sizes (0.1, 0.25, 0.5 and 1.0 ha) to assess the importance of scale for correlation with radar backscatter. Fig. 1 depicts the sampling of forestry data across forest reserve types for Sabah. The black crosses delineate placement of forest inventory transects, black squares indicate forest plots and red[1] squares show the location of oil palm plantation plots.

Table 1 lists the land cover classification and number of hectares of data collected for all plots and transects. The most useful height variables are those that were able to effectively differentiate between the unlogged (UNL) and logged forests (L70–L03) as well as oil palm (OP-I and OP-M) and timber plantations (SSSB-I and SSSB-M). The disturbance values FRCL, FRCM and FRCH are kept

[1] For interpretation of color in Figs. 1 and 6, the reader is referred to the web version of this article.

separate as no data were provided as to when these areas surveyed had been disturbed or logged; however soil data and forest type were provided and are included. Immature plantations were 3 years or younger for oil palm and 2 years or younger for timber. Mature oil palm plantations measured ranged from 4 to 19 years after planted and mature timber plantations ranged from 3 to 6 years after planted. The companies managing the oil palm and timber plantations provided data on age.

Height measurements were not made for all trees due to time constraints and dense canopies and, for the case of FRC data, were not collected at all. For sub-sampled heights logarithmic allometric equations were generated in relation to measured DBH, in order to calculate height values for the entire transect (see Fig. 2 for an illustration). Three height equations were generated for (i) trees of DBH 10–20 cm and (ii) greater than 20 cm and (iii) for all measured trees per plot combined. The first two equations are consistent with recommendations made by Návar (2009) due to the inflection point between small- and large-diameter trees in this relationship. For the datasets without any height measurements from which to calibrate, equations were generated using all trees

Table 1
Disturbance values for plot and transect data with number of hectares sampled.

Forest reserve	Disturbance values	Description	Hectares
Danum Valley and Sepilok	UNL	Unlogged forest	14.0
Malua	L70	Logged forest (~1970)	5.0
	L07	Logged forest (2007)	3.0
Ulu segama	L88	Logged forest (1988/9)	13.0
Deramakot	L95	Logged forest (1995/6)	2.0
	L00	Logged forest (2000/2)	4.0
	L03	Logged forest (2003/6)	4.0
Lower kinabatangan floodplain	FRCL	FRC low[a]	5.1
	L-LMDF	Lowland Mixed Dipterocarp Forest (MDF)[L]	3.1
	L-PSF	Peat Swamp Forest[L]	2.0
	FRCM	FRC moderate[a]	1.6
	M-PSF	Peat Swamp Forest[M]	1.6
	FRCH	FRC high[a]	66.9
	ESF	Early Secondary Forest (ESF)-MDF	4.5
	SF	Secondary Forest-MDF and limestone	7.5
	L-LSF	Late Secondary Forest (LSF)-MDF	13.4
	R-ESF	Riparian (ESF)	5.2
	R-LSF	Riparian	6.3
	H-LMDF	Lowland Mixed Dipterocarp Forest[H]	10.9
	H-PSF	Peat Swamp Forest(LSF/ESF)[H]	19.1
PPB Plantations	OP-I	Oil palm (immature)	0.75
	OP-M	Oil palm (mature)	4.25
Sabah Softwoods	SSSB-I	Timber plantation (immature)	1.0
	SSSB-M	Timber plantation (mature)	2.0
	Total		126.7

[L] = "low" disturbance, [M] = "moderate" disturbance, and [H] = "high" disturbance.
[a] 'FRC' refers to the Forestry Research Centre, the research arm of the Sabah Forestry Department. The designation low, moderate and high was provided by the FRC to describe the level of disturbance of their sites.

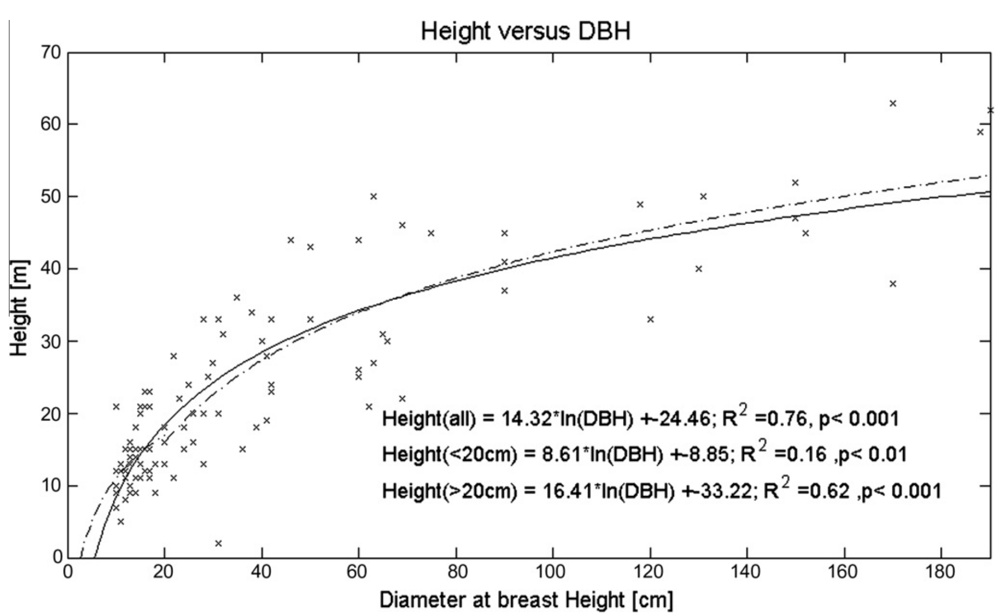

Fig. 2. Relationships between measured height and DBH. Generated logarithmic allometric equations from measured height values in the field. Equations are color-coded with size classes from which they were generated.

Table 2
Biomass variables generated from allometric equations in the literature. D refers to diameter at breast height (in cm), H refers to height (in m) and ρ refers to wood density (g cm^{-2}). H_1 and H_2 refer to the equations derived for height estimates described above. Finally, AGB estimates are in kg.

Biomass value	Derived for	Equations	References
Biomass A	Moist forest ρ = 0.5	$\rho \times e^{(-1.499+2.148\times\ln(D)+0.207\times(\ln(D))^2-0.02081(\ln(D))^3)}$	Chave et al. (2005)
Biomass B	Moist forest ρ from literature	$\rho \times e^{(-1.499+2.148\times\ln(D)+0.207\times(\ln(D))^2-0.02081(\ln(D))^3)}$	Chave et al. (2005)
Biomass C	Moist forest ρ from literature	$0.0509 \times \rho \times (D^2) \times H_1$	Chave et al. (2005)
Biomass D	Moist forest ρ from literature	$0.0509 \times \rho \times (D^2) \times H_2$	Chave et al. (2005)
Biomass E	Asian moist forest	$42.69 - 12.8 \times (D) + 1.242(D^2)$	Brown (1997)
Biomass F	Asian moist forest	$e^{(-2.134+2.530\times\ln(D))}$	Brown (1997)

measured in logged forest to create a “generic” allometric equation for disturbed lowland forest. This practice did add another level of error to the biomass estimates in these plots that is discussed later. These height values were then used over the transect, sub-transect or plot level to calculate the relevant average height and dominant height values (the average height of trees in the top 20% of DBH values).

Estimates of biomass values were calculated using several allometric equations. This was to compare the variety of available equations in the literature relevant to this region, which provided a significant range in biomass estimates and indicate a need for consensus in the research community regarding which equations should be used for subsequent AGB studies. Table 2 provides a list of the equations used, what dataset they were derived from and the references from which they were taken. Biomass equations A–D were developed for pan-tropical moist forest (predominantly South American and Asian forest; with no data from Africa) (Chave et al., 2005). Equations A and B only use wood density and DBH data. Equation A applies a plot mean wood density of 0.5 g cm^{-3}, while equation B uses the specific wood density value found in the literature for tropical species (average value), genus or family (depending on the ability to identify to species in the field or availability of species-specific or genus-specific wood densities). Equations C and D include height estimates, which reduce errors in above ground biomass (AGB) estimates from 19.5% to 12.5% (Chave et al., 2005). Finally, biomass equations E and F were derived from 170 destructively sampled trees in moist tropical forests in Asia by Brown (1997).

Biomass equations used for oil palm estimates were taken from Henson and Chang (2003) and Corley and Tinker (2003), which are listed in Table A.1 (in the Appendix). The biomass equation for Corley and Tinker was used with data collected in the field, while Henson's equation assumes an “average oil palm” plantation of approximately 128–140 palms ha^{-1} (the range in values is due to palm mortality as the canopy closes), depending on years since planting. Some subsequent studies have found Corley and Tinker's equations underestimate oil palm biomass by 10% (Corley, *pers comm.*); while this was taken into consideration for this study it was not deemed a significant source of error.

2.3. ALOS-PALSAR data

Eight scenes of ALOS PALSAR FBD imagery, acquired in September/October 2008, were used for this study. The level-1.5 acquired images were processed to σ^0 (power) values, 30-m resolution and terrain corrected using the Alaska Satellite Facility's (ASF) Mapready software and a 90-m Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) (Jarvis et al., 2006). Within the Mapready software, power values were calculated from raw digital numbers (DNs) using Eq. (1) from Shimada et al. (2009):

$$\sigma^0 = 10 \times \log_{10}(\text{DN}^2) - 83 \tag{1}$$

The images were then ortho-rectified to Universal Transverse Mercator (UTM) projection using Landsat ETM$^+$ imagery, with a root mean square error (RSME) of <0.65 Landsat pixels (30 m). Finally, a three-pixel, enhanced Lee filter was applied to reduce speckle in the images (Lee, 1980). For maximum likelihood classification (MLC) analysis a three-band image was analyzed, which consisted of bands HH, HV and a ratio of HV/HH. The ratio was used in order to reduce topographic effects, which have significant impacts on SAR backscatter. This is based on the principle from optical data that each band interacts with topographic elements similarly and that by taking the ratio of the two bands the interference due to these undulations can be minimized. For the final biomass map the images used were resampled to 100-m (1-ha) resolution to match the scale of the derived regression relationship.

SAR data acquired on different dates are also impacted by changes of surface moisture due to precipitation (Mitchard et al., 2009). The presence or absence of precipitation was established using the Advanced Microwave Scanning Radiometer – Earth Observing System (AMSR-E) rainfall dataset (Adler et al., 2007). As this imagery had a resolution of 5 km, pixels were extracted for entire forest reserves or sampled areas (see Fig. A1). AMSR-E images were acquired for each date of ALOS-PALSAR imagery. Unfortunately there was no AMSR-E coverage of our study site for September 9, 2008; therefore, meteorological data was requested for the Danum Valley Conservation Area (DVCA) revealing a significant rain event of 32 mm (Walsh, 2009).

3. Results

3.1. Ground data

3.1.1. Differentiation of disturbance levels by height estimates

Due to the range of plot sizes available for analysis, plot-level mensuration variables were plotted as histograms to assess their changes in distribution with increasing plot size (see Fig. A2). The evolution of average height values across plot size were illustrative, showing reduced variation with increasing plot size across disturbance levels indicating it was not an effective means of distinguishing between them. Dominant height showed a better distribution across plot sizes (not pictured), indicating it might be a better variable for differentiation of disturbance level.

3.1.2. Estimation of aboveground biomass

Greater attention has been paid to the propagation of error for above ground biomass (AGB) estimates via the choice of allometric equation used. Measurement errors for diameter, height and wood specific gravity (i.e. density) may be significant at the tree-level AGB estimate, but are almost negligible relative to the use of generalized allometric equations for plot-level estimates (Chave et al., 2004). After analysis of wood density values, it became evident that 0.5 g cm^{-3} was not a reasonable assumption for wood density in this region (e.g. Chave et al., 2005). Studies in both Borneo and the Amazon have used values of 0.67 (Chave et al., 2006; Fearnside, 1997; Paoli et al., 2008). We found the mean weighted wood density across forested plots to be 0.6, which is consistent with

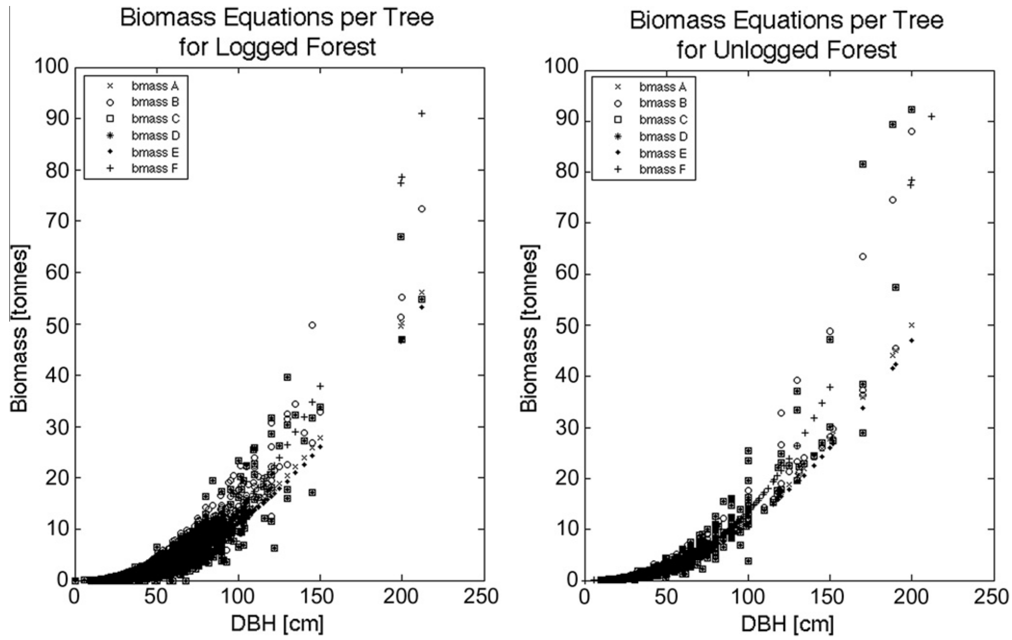

Fig. 3. Evaluation of biomass equations. Equations A–F are compared using per tree calculations of biomass (in Mg) across all DBH values (in cm). (Left) Presents biomass estimates for logged forest and (right) presents estimates for unlogged forest.

Ketterings et al. (2001) average wood density across species in Sumatra.

An evaluation was performed of the six chosen biomass equations (see Fig. 3) to assess the range in values. The large discrepancy in these estimates becomes more evident for trees with DBH larger than 80 cm. Equations B–D appear to have the highest estimates for mature/unlogged forest while equation F are the highest for logged forest. Using equation A as the median estimate for biomass, percent differences were calculated for a subset of equations for both logged and unlogged forest plots (see Table 3). The inclusion of wood density estimates for equation B yields higher biomass estimates for both size classes, while the inclusion of height values in equation C produces higher estimates for larger trees particularly in unlogged forest. This range in values seems to be due to the difference in assumption of height values for logged-over areas.

Including height estimates for AGB calculations is particularly important for this region (see Fig. A3 in the Appendix). Plotting the difference between estimates from equations B and C over equation B values showed the addition of height measurements in mature forest added an overall positive bias to biomass estimates, while the opposite was true for logged forest. This finding has implications for future biomass estimates in this region, as timber extraction favors the removal of the tallest trees (i.e. members of the family Dipterocarpaceae), which reach heights greater than 80 m, significantly greater than are found in the Neotropics and Africa. Therefore, the equations that included DBH, wood density and height were assumed to be the most appropriate for subsequent analyses, particularly for plots where height had been measured.

Table 3
Percent difference in per tree biomass estimates from equation A for two different tree size classes and two different disturbance levels. Negative values indicate lower estimates and positive values refer to higher estimates.

Disturbance level	DBH range	Percent difference from Eq. (1)			
		Eqn B	Eqn C	Eqn D	Eqn F
Logged forest	10–60 cm	0.16	−0.09	−0.09	0.11
	>60 cm	0.17	0.02	0.02	0.12
Unlogged forest	10–60 cm	0.24	−0.03	−0.03	0.12
	>60 cm	0.13	0.12	0.12	0.15

3.1.3. Relationship between AGB and forest structural metrics

Average height was a reasonable predictor of AGB while dominant height was significantly worse (see Fig. A4, in the Appendix); although, average height variables were less reliable than relationships generated by Köhler and Huth (2010) from canopy height. It was surprising that dominant height was the worse predictor considering it was better at differentiating between disturbance levels. Unsurprisingly, both height variables had higher correlations with equation C, which includes height measurements. The use of generalized allometric height equations in areas without *in situ* height measurements (i.e. data provided by FRC) made those estimates less reliable; however, values for equations B and C were used for comparison during subsequent analyses with SAR backscatter values.

For oil palm plantations, Fig. 4 presents four biomass estimates for field measurements, (i) Corley and Tinker's equation using collected field data (ii) Corley and Tinker's equation increased by 10%, (iii) Henson's ideal per hectare biomass estimate including belowground biomass and (iv) Henson's ideal per hectare biomass estimate without belowground biomass. Once the belowground biomass factor was removed, Henson's equation was consistent with field-measured data. The AGB in oil palm plantation actually decreases after 20 years due to abscission of frond bases as the palms mature. Corley and Tinker's equation with un-augmented biomass estimates was used with subsequent SAR analysis. Fig. 4 also presents the increase of AGB with age for the two timber species sampled. *A. mangium* is used predominantly for pulp and paper while *A. ferrucania* is sold as round logs, consistent with the slopes of their respective regressions.

3.1.4. Biomass estimates for different disturbance levels

Table 4 presents the mean biomass estimates for each disturbance level and their variability as a percent of the mean,

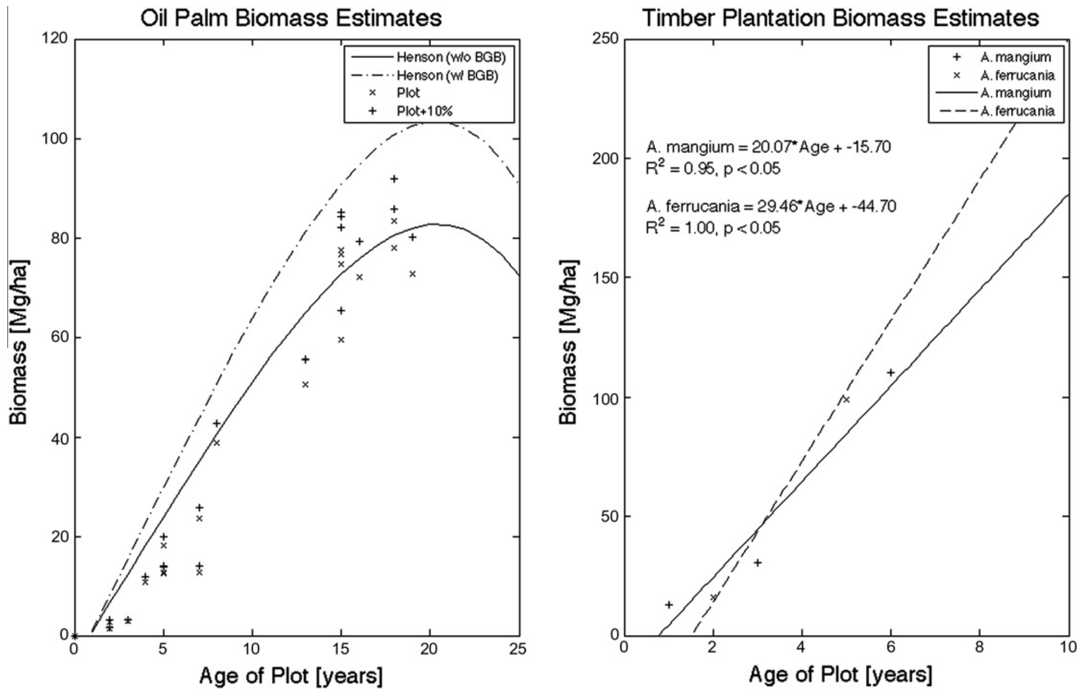

Fig. 4. Oil palm AGB estimates. (Left) Field measured palm oil biomass estimates compared to Henson's assumed per hectare estimates relative to age. *Plot* refers to field measured values and *plot* + 10% refers to a 10% increase in the biomass estimate to correct for reported underestimates by Corley (as discussed above). The AGB decreases after 20 years due to abscission of frond bases as the palms mature. (Right) Field measured timber plantation biomass estimates for *Acacia mangium* and *Albizia ferrucania*.

Table 4
Mean biomass values using equation B across 1 ha plots of each disturbance value, with variability in estimates across plots.

Disturbance values	Description	Number of plots	Size of plots [ha]	Mean biomass value [Mg/ha]	Variability across plots [% of mean]
UNL	Unlogged forest	14	1.0	353	14
L70	Logged forest (~1970)	4	1.0 and 1.5	287	14
L88	Logged forest (1988/9)	13	1.0	187	11
L95	Logged forest (1995/6)	2	1.0	299	1
L00	Logged forest (2000/2)	4	1.0	361	14
L03	Logged forest (2003/6)	4	1.0	203	5
L07	Logged forest (2007)	2	1.5	244	29
L-LMDF	Lowland mixed Dipterocarp forest (MDF)[L]	3	1.0 and 2.0	216	22
L-PSF	Peat swamp forest[L]	2	1.5	128	2
M-PSF	Peat swamp forest[M]	1	1.5	66	0
ESF	Early secondary forest (ESF)-MDF	3	1.3 and 1.5	130	13
SF	Secondary forest-MDF and limestone	6	1.5 and 2.0	114	16
L-LSF	Late secondary forest (LSF)-MDF	9	1.5, 2.0 and 5.0	110	15
R-ESF	Riparian (ESF)	5	2.0	176	21
R-LSF	Riparian (LSF)	4	1.0, 1.5 and 2.0	149	7
H-LMDF	Lowland mixed Dipterocarp forest[H]	7	1.5 and 2.0	128	2
H-PSF	Peat swamp forest (LSF/ESF)[H]	14	1.0, 1.5 and 2.0	104	16
OP-I	Oil palm (immature)	3	0.25	2.4	19
OP-M	Oil palm (mature)	17	0.25	52	15
SSSB-I	Timber plantation (immature)	2	0.5	15	12
SSSB-M	Timber plantation (mature)	4	0.5	116	34

[L] = "low" disturbance, [M] = "moderate" disturbance and [H] = "high" disturbance.

calculated from equation B for 1.0 ha estimates. The key values to note are the significant differences between immature and mature oil palm plantations with all forest covers, except for immature timber plantation. While the maximum AGB value for oil palm plantations may approach 100 Mg ha^{-1}, taking the average value over the life of the plantations reduces this value significantly, by 50% in the case of this study or 25% (~74 Mg ha^{-1}) using a generalized relationship like Henson's. All other forest AGB estimates exhibit variability ranging from 5% to 21% of mean values, although when arranged in degree of disturbance they show a clear decreasing trend in AGB from unlogged to severely degraded forest (see Fig. 5). There is a clear division between the severely degraded forest areas measured by the FRC compared to the commercial forest reserves sampled for this study (all logged plots with years). The former rarely reach above 150 Mg ha^{-1}, the highest AGB values from this dataset being in low disturbance, lowland mixed dipterocarp forest. While most managed and protected forests store well above 200 Mg ha^{-1}. This discrepancy in AGB values indicates there

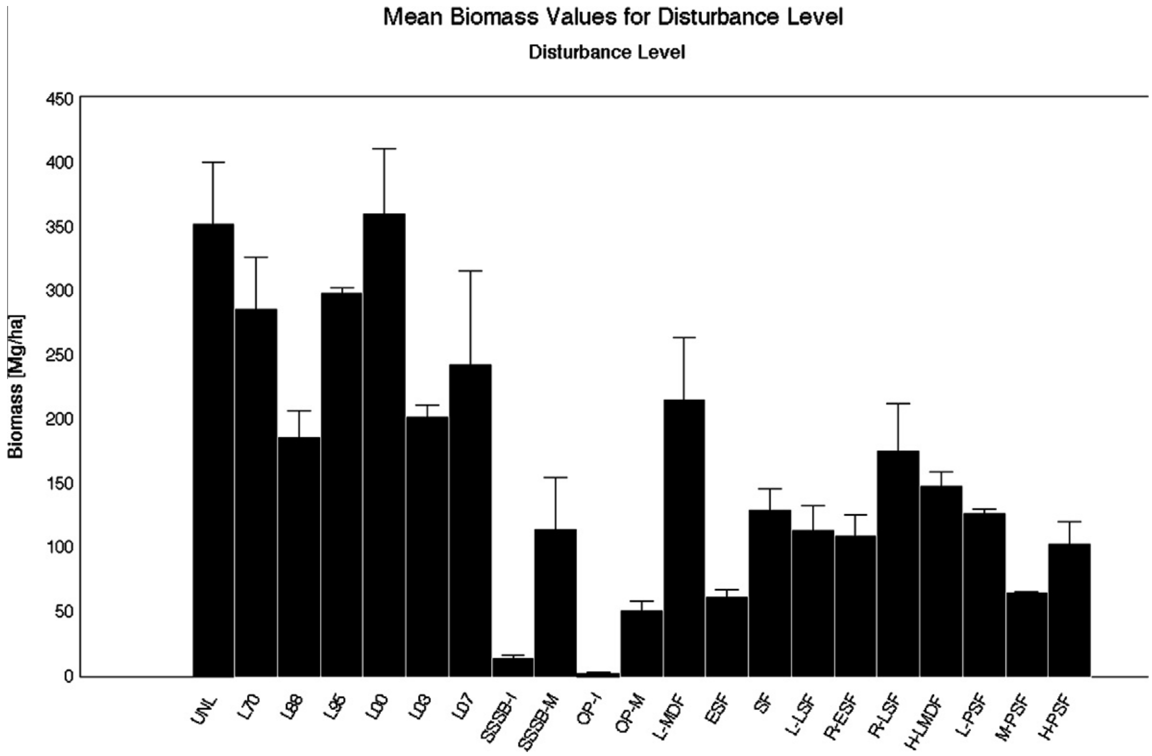

Fig. 5. AGB estimates across disturbance levels. Mean plot biomass values and standard error (variability of plot values) for each disturbance level analyzed.

would be a significant difference in AGB change estimates from conversion of logged forest of different disturbance levels to oil palm plantation.

3.2. ALOS PALSAR analysis

3.2.1. Discrimination of oil palm and forest pixels

Due to the interaction of L-band SAR data with leaves, branches, and stems of vegetation, it was assumed PALSAR FBD data would be able to differentiate between regular spaced oil palms in a plantation and more randomly located trees in forested areas. This was assessed using the maximum likelihood classifier (MLC) supervised classification technique and the three band ALOS imagery (HH, HV and HV/HH), using coordinates for sampled oil palm plantations and forest areas of >150 Mg ha^{-1} AGB estimates. Half of the ground control points were used for training and the second half for testing the MLC layer. Alberga (2007) showed MLC to be a reasonably reliable classification technique with SAR data, although concerns have been raised of the textured nature of SAR data being inappropriate for clustering algorithms that depend on probability density functions (Sgrenzaroli et al., 2004; Simard et al., 2000). Fig. 6 shows classified forest pixels in green and oil palm plantations in red with an accuracy of 97.0% and a κ coefficient of 0.64. Where the κ coefficient measures the accuracy of a classification layer accounting for pixels classified correctly by chance (based on values of observed accuracy and expected accuracy). Table 5 shows the producer's and user's accuracy of the classification. Attempts to perform MLC analysis on three classes (intact forest, >250 Mg ha^{-1}, logged, 150–250 Mg ha^{-1} and oil palm plantation) were not successful with a greatly reduced accuracy of 44.2% and a κ coefficient of 0.09.

3.2.2. Relationships between AGB and PALSAR backscatter

We performed logarithmic regression analysis for each forest reserve for three variables (dominant height and AGB from equations B and C) and both FBD bands (see Table A.2). HH-polarized backscatter proved to be a poor predictor of most of the three variables; although, occasionally showing significant correlation with dominant height. HV-polarized backscatter fared better, with its

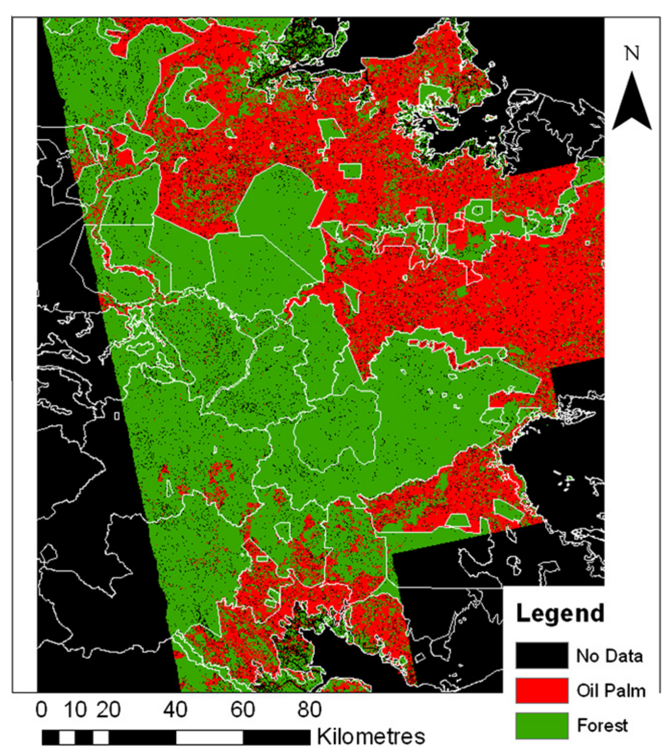

Fig. 6. Map of forest and oil palm. Supervised classification (using MLC) of 3-band mosaic (HH, HV and HV/HH) for two classes, oil palm and forest pixels (accuracy = 97.2%, κ = 0.65).

Table 5
Assessment of classification accuracy for MLC.

Confusion matrix results	ALOS (2008)	
	Oil palm	Forest
Producer's accuracy (%)	100.0	97.0
User's accuracy (%)	54.0	100.0
Overall accuracy (%)	97.0	
Kappa coefficient	0.64	

best relationships with both AGB equations. Unfortunately, dominant height was rarely correlated; indicating it would not be effective for differentiating between disturbance levels using SAR data.

At this level of analysis, it was unclear whether the inclusion of height in equation C improved the relationship between AGB and backscatter, although its significance was greater for all plots except timber plantations (SSSB). This analysis does show that low AGB and the less intact canopy of the Sabah Softwoods timber plantation allowed for highly significant regression relationships and revealed the importance of having a range of biomass values from low to high for effective relationships to be derived. Finally, while these data are able to differentiate forest and oil palm successfully, the use of single HV-based algorithm was not successful in estimating AGB in oil palm plantations. However, it has been shown that similar to ground-based allometric equations, forest type-based algorithms are more effective in estimating biomass of oil palm plantations (Koay et al., 2009; Nordin et al., 2002). We did not pursue developing a separate algorithm for oil palm plantations due to an insufficient number of plots.

Regarding the impact of precipitation, it is evident that all correlations estimated from imagery acquired on September 9, with documented extremely high precipitation, are severely reduced. We found that comparing analyses of two images of the Malua plots showed significant improvement in the drier, September 26, image. Therefore, the most reliable relationship was derived for forest plots not affected by precipitation (e.g. Malua, Sabah Softwoods and Deramakot) and acquired on the same day (September 26). The inclusion of Kinabatangan plots significantly weakened the relationship, which may have been due to poor global positioning system (GPS) correlation with forest plots and/or a precipitation event not captured by the AMSR-e data. Biomass estimates for all six allometric regression equations of the 22 plots used are presented, including the mean of these values and their standard deviation (see Table 6). These are presented in order to include the inherent error in these estimates before calculating root mean square errors (RMSE) for derived equations.

3.2.3. Potential of ALOS-PALSAR to estimate AGB

Using the plots presented in Table 6, logarithmic regressions were attempted for AGB estimates for equations B and C. RMSE values were then calculated for both relationships using the same data points (see Fig. 7). For both measures equation B fared significantly better, while its R^2 value was only marginally improved, the ability of this regression to predict AGB was superior. Looking at the comparison of predicted to measured AGB, both relationships seem to underestimate AGB values. We assessed the saturation points for both equations and found that equation B saturated at AGB levels of 88 Mg ha^{-1} and equation C was at approximately 80 Mg^{-1}. Nevertheless, the RMSE in both relationships was large, indicating that even without attenuation from precipitation areas of AGB values greater than 100 Mg ha^{-1} are not well modeled.

Finally, using the relationship derived for equation C and the HV-polarized band (see Eq. (2)) an initial attempt at a biomass map of Sabah (with oil palm areas removed) is presented (see Fig. 8).

$$\mathrm{AGB} = \exp\left(\frac{\mathrm{HV} - 0.013196}{0.0080139}\right) \tag{2}$$

The accuracy of this map, $R^2 = 0.35$ and RMSE = 125 Mg ha^{-1} (derived from non-precipitation affected plots with <450 Mg ha^{-1} AGB values), was calculated from 37 plots not affected by precipitation. With the saturation of the signal above 88 Mg ha^{-1}, it is difficult to reliably differentiate between biomass classes of 150–250 Mg ha^{-1} and greater than 250 Mg ha^{-1}. Also the areas with the most topography appear to have the lowest biomass values, which may again be a limitation caused by the sensitivity of side-looking SAR backscatter to topographically complex terrains and potentially the use of poor terrain correction approaches in

Table 6
AGB estimates for each plot used for generating the final predictive relationship from the HV band. Estimates were calculated from allometric regression equations listed in Table 1 and are in Mg ha^{-1}. A mean of these estimates and their standard error as a percent of the mean are also reported.

Forest reserve	Plot number	Disturbance value	Eqn A [Mg ha^{-1}]	Eqn B [Mg ha^{-1}]	Eqn C [Mg ha^{-1}]	Eqn D [Mg ha^{-1}]	Eqn E [Mg ha^{-1}]	Eqn F [Mg ha^{-1}]	Mean [Mg ha^{-1}]	Std. Dev. [% of mean]
Malua	1	L70	318	381	305	308	371	345	338	10
	2	L70	223	262	224	225	247	252	239	7
	3	L70	202	194	161	161	223	232	196	15
	4	L70	282	312	213	219	323	316	277	18
	5	L07	150	172	124	123	170	167	151	15
	6	L07	264	316	262	262	310	298	285	9
Sabah Softwoods	1	SSSB-M	27	31	22	22	32	35	28	18
	2	SSSB-I	11	13	7	7	14	20	12	42
	3	SSSB-I	13	16	9	9	15	17	13	31
	4	SSSB-M	177	222	175	174	191	224	194	12
	5	SSSB	80	99	82	82	89	106	90	12
	6	SSSB	97	110	120	120	107	127	114	10
Deramakot	1	L95	266	295	206	204	294	298	260	17
	2	L95	255	303	240	227	286	287	266	11
	3	L00	270	350	249	249	300	304	287	14
	4	L00	413	503	422	422	467	453	447	8
	5	L00	277	328	219	264	305	315	285	14
	6	L00	214	263	243	241	238	243	240	7
	7	L03	168	203	184	184	185	193	186	6
	8	L03	170	199	171	171	188	190	181	7
	9	L03	149	182	165	165	165	168	166	7
	10	L03	193	228	230	232	219	208	218	7

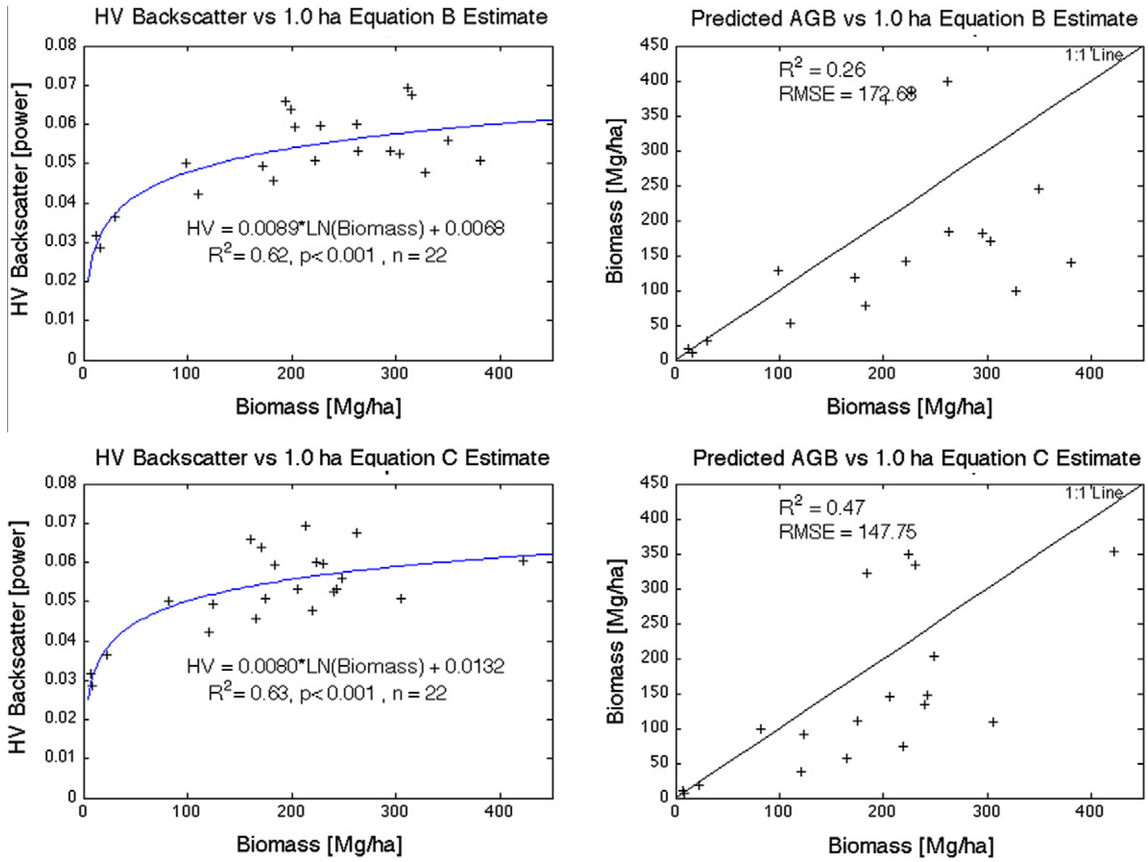

Fig. 7. Relationship between SAR backscatter and AGB. Logarithmic regression between HV-backscatter and measured AGB estimates (left column) from equation B (above) and from equation C (below). The *n* values refer to the number of hectares used to generate the relationship (plot numbers listed in Table 6). Assessment of predictive power for each relationship is presented by plotting predicted AGB on the *y*-axis and measured AGB on the *x*-axis (right column).

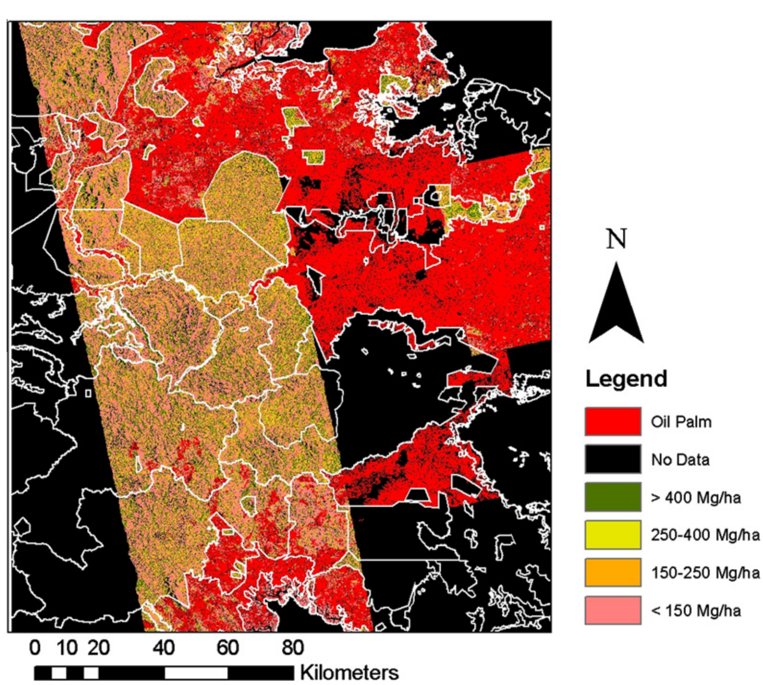

Fig. 8. Biomass map of Sabah. Biomass values were generated only from non-precipitation affected imagery. Oil palm areas were derived from all images and are pictured in red. Biomass values have been grouped for all high biomass areas (>250 Mg ha^{-1}), moderate biomass areas (two groups from 50 to 250 Mg ha^{-1}) and severely degraded areas (<50 Mg ha^{-1}) (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

PALSAR processing. This map also suffers from a large area of missing data due to the heavy level of precipitation on September 9. This analysis would benefit from comparing ground data with imagery of another date or the use of multiple data to capture the variability of precipitation effects on the SAR data.

4. Discussion

4.1. Relationship between AGB and forest structural metrics

Average height values did not change significantly across disturbance level, but exhibited a stronger relationship with biomass compared to dominant height. This was surprising considering that biomass did change across disturbance levels. It appears that neither of these height variables would make a reliable estimator of plot biomass levels, however other studies have had more success relating height variables to AGB. Saatchi et al. (2011) have found significant relationships using Lorey's height. Köhler and Huth (2010) used a process-based, forest-growth model parameterized for this region, FORMIND2.0, which shows strong correlation between canopy height and AGB in modeled primary and logged forest as well as permanent sampling plots.

4.2. Estimation of aboveground biomass

In order to effectively map AGB using remote sensing techniques, it is important to first have a reliable biomass value. Considering the range of biomass estimates that can be calculated for the same tree, the choice of allometric regression equation and measured input data are critical. Tropical Asian forests, with many tall trees are not well described by allometric equations developed for other tropical regions (e.g. the Americas). The inclusion of height measurements across DBH size classes proved an important factor for biomass estimation when using equations A–D, which are generalized for the tropics. Unfortunately for this study, there were not *in situ* height measurements for all sampled plots, thereby reducing the reliability of biomass estimations of these plots from equation C.

Measured biomass for oil palm plantation plots compared well with modeled oil palm growth, developed by Henson, especially when belowground biomass estimates were removed. Modeled biomass accumulation for each species in timber plantation plots, although fewer in number, exhibited interesting characteristics. The *A. mangium* plots exhibited a higher slope, consistent with its use as a fast-growing, low-density wood for pulp and paper manufacture. The *A. ferrucania* plots, where trees were grown for board production, showed a slower biomass accumulation function. These relationships are only based on 3 ha worth of data and therefore are only useful for illustrative purposes.

Finally, plot size was also an important factor to consider, when collecting field data and relating it to SAR backscatter. Generally the 1 ha plots proved to be the most reliable plot size, less prone to errors due to expansion of mensuration variables from smaller areas, impact of geolocation errors, and exhibiting the strongest relationships with PALSAR backscatter. Also, there were advantages of square plots over line-transects, due to the heterogeneous nature of forested landscape being monitored and the unavoidable GPS errors from interference of dense canopies. As a result, averaging of several contiguous pixels for one plot would be preferable to the same number along a single line. At the same time, the line transects were considered preferable for a rapid assessment of variation within an area of similar management, which would not have been possible solely with randomly located 100 by 100 m plots. Therefore, a combination of these two sampling types could be implemented for future studies.

4.3. AGB estimates for different disturbance levels

Estimating average biomass values for each disturbance level, the values in Table 4 exhibit a large variation partially due to the arbitrary nature of their grouping and also the relative sample size of each level. The unlogged forest areas do exhibit among the highest levels of biomass, although some selectively logged forest plots do approach similar levels, depending on time since the forest was logged, intensity of logging and soil characteristics. The latter, while not considered for this study, has been shown by Slik et al. (2010) to be an important factor influencing forest characteristics, such as AGB. There is a large difference in AGB values for most forested areas and oil palm plantations, indicating most forest conversions to oil palm would result in a net carbon loss. The AGB of older timber plantations does approach that of some of the degraded forest areas, making distinction of these areas by biomass values more difficult. Finally, AGB values for disturbed peat swamp forest are relatively low, though these sites are known to contain large belowground reserves of carbon.

4.4. Discrimination of oil palm and forest pixels

This study has shown that the PALSAR FBD-polarized data is able to differentiate between forest and oil palm plantation reliably, making it a useful sensor for monitoring conversion of forest to oil palm (Koh et al., 2011); however, as it is no longer operational, its use is limited until a similar sensor is launched to continue this monitoring service. The user's accuracy for oil palm reveals an overestimation of classified oil palm areas, due to confusion with swamp forest or forest inundated with water. Additionally, the scattering of large leaves of oil palm trees appears to obscure any information on the palms' AGB using the same HV algorithm developed from all forest plots, suggesting the use of different algorithms will be needed for mapping AGB of oil palm plantations (Koay et al., 2009; Nordin et al., 2002). We expect the increasing interest in ground inventory of oil palm plantations will provide the necessary data to develop oil palm specific algorithms. Monitoring of changes in forest cover and expansion of oil palm plantations has become possible with the use of frequent and cloud-free ALOS-PALSAR observations over the past few years (2006–2011) (Koh et al., 2011); however, detecting changes in oil palm areas prior to ALOS data requires combining data from past SAR satellites (e.g. JERS) with only HH-polarized data (Rosenqvist, 1996). Also, as conversion of forest to oil palm in Malaysia is slowing; this type of monitoring would be more useful for forest loss in Indonesia, the current site of oil palm expansion.

4.5. Relationships of AGB and mensuration data with PALSAR backscatter

As outlined before, height was an important metric to include for AGB estimation from allometric regression equations; this remained true for relating estimates to SAR backscatter. Table 6 revisited AGB estimates for all equations generated solely or partially from Asian forest data, showing the range in AGB values possible for each plot used to generate the final SAR relationship. Assessment was performed for all of these estimates (results not shown); however, equation C was consistently the strongest relationship. Therefore, the logarithmic regression derived between the HV band and 1 ha biomass estimates for equation C, appears to be reasonably reliable ($R^2 = 0.63$, $p < .001$); however the RMSE values are very high. This would be due partially to the relationship saturating at 88 Mg ha^{-1} AGB values making it difficult to map areas of AGB significantly higher than that, which were the majority of forest plots for this study. This shortfall is consistent with previous studies that have found limitations in using L-band SAR data to map biomass values >100 Mg ha^{-1} (Mitchard et al., 2009; Saatchi et al., in press); however, studies that have considered the impacts of precipitation have increased saturation levels to well above 150 Mg ha^{-1} (Englhart et al., 2011). While L-band SAR data has shown reasonable relationships with biomass, P-band SAR data has much higher correlations to higher biomass values (Le Toan et al., 1992; Saatchi et al., 2007a) due to its greater penetration in the vegetation and stronger sensitivity to stem biomass (Waring et al., 1995). Unfortunately, no current satellite sensors emit P-band microwaves (Patenaude et al., 2005), although the European Space Agency (ESA) is in the process of developing one as part of their BIOMASS Earth Explorer mission.

4.6. Potential of ALOS-PALSAR to estimate AGB

Changes of environmental conditions such as soil and vegetation moisture can impact SAR backscatter data. In performing the analysis over the study area, we did not account for these effects in SAR backscatter and hence did not acquire multiple data over the same area. We, therefore, expect an unquantifiable part of the errors in estimating the forest biomass is due to the effect of precipitation. Any future SAR studies in this region will need to consider this and acquire data over multiple seasons to reduce the effect and improve the biomass estimation (Englhart et al., 2011). As Sabah's monthly precipitation rarely drops below 100 mm, even during its dry season (Slik et al., 2010), precise monitoring of forest cover change or AGB requires multiple radar acquisitions that are often available with the ALOS-PALSAR and, hopefully, future sensors.

The saturation of L-band imagery for AGB levels, at best, less than 150 Mg ha^{-1} will also greatly reduce the ability to adequately estimate degradation of forest in this region due to pressures such as timber extraction; however, estimation of forest AGB loss to oil palm conversion should be possible for lowland areas of low to moderate topography, especially where forests have been severely degraded in advance. Therefore, studies of land cover change and biomass estimation around oil palm cultivation in this region would benefit from using ALOS-PALSAR FBD data.

Finally, algorithms developed from polarimetric data and designed to capture the specific structural variations in forests have potentially more capability to estimate the biomass of different forest types accurately. These advanced techniques include using fully polarimetric SAR and texture analysis (Hoekman and Quiñones, 2002; Saatchi et al., 2007a, 2000), fusion of radar and optical sensors (Kellndorfer et al., 2010; Moghaddam et al., 2002), fusion of L-band and X-band radar (Englhart et al., 2011), or SAR Interferometry techniques (Treuhaft et al., 2004).

5. Conclusion

This study has accomplished two of its three aims, being unable to map AGB in oil palm plantations. It has also highlighted some of the limitations to monitoring this region with SAR data, due to the high AGB values in unlogged and secondary forest as well as the difficulty in avoiding rain events. Similar studies in savannah forests of Africa have shown much higher degrees of correlation (Mitchard et al., 2009), both due to the relatively lower range of AGB levels and drier state of the vegetation. Unlogged and secondary forest are difficult to differentiate, owing to the saturation in the signal; however in terms of conservation value there may be little difference between the two (Berry et al., 2008), particularly relative to the comparison to degraded forest and oil palm plantation (Edwards et al., 2010). It has also highlighted the limitation of existing allometric equations if height information is not incorporated; therefore, we suggest future studies in this region should try to include this factor. For this study it was noteworthy that plot average height and dominant height were not well correlated with biomass nor was dominant height correlated with the SAR backscatter; therefore, this study would conclude that efforts to model height from SAR data as a proxy for AGB may be difficult. However, this is not consistent with recent results using modeled data (Köhler and Huth, 2010), SAR data (Saatchi et al., 2011), and Lidar sensors (Lefsky et al., 2002), which used different plot level height metrics in AGB estimates.

This analysis has shown the HV-polarized band to be preferable for forest monitoring, while the HH-polarized band shows higher sensitivity to environmental variables. The results also imply that the use of a single algorithm from radar channels is not recommended for biomass estimation of structurally different forest types. While several plot sizes have been used in other studies, this analysis demonstrated the benefit of collecting data at the 1 ha scale, in order to reduce the errors propagated through extrapolation from smaller areas. This is especially a concern for small forest plots with large trees, not uncommon in dipterocarp-dominated forest. However, the reliance on data collected at the 1 ha scale will result in limited ability for SAR data to adequately capture smaller-scale disturbances. Due to the need to reduce speckle effects of SAR data (by reducing resolution) and the inherent error in AGB estimates for tropical forests (where allometric regression equations have not been developed for each species) that are best averaged out in larger plots (Saatchi et al., in press). However, existing high resolution airborne and spaceborne SAR sensors (e.g. NASA's UAVSAR, and the German Terra XSAR sensors) with pixels sizes of 1–5 m will provide new capability to monitor small scale changes in forest structure and cover. Finally, ALOS-PALSAR has been shown to have the potential to be an excellent dataset for monitoring oil palm expansion in this region, as oil palm plantations have such a distinguishable signal from forest. It appears difficult to provide reliable estimates of biomass loss, through ALOS-PALSAR data alone, however. Future approaches may need to combine maps based on another L-band sensor with optical sensor data to improve estimates of changes in AGB.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.foreco.2011.07.008.

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