DEVELOPING SITE-SPECIFIC ALLOMETRIC EQUATIONS FOR ABOVE-GROUND BIOMASS ESTIMATION IN PEAT SWAMP FORESTS OF ROKAN HILIR DISTRICT, RIAU PROVINCE, INDONESIA

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ABSTRACT

In forest biomass assessment studies, the selection or development of reliable allometric biomass equations is an essential step which determines largely the accuracy of the resulted biomass estimates. Unfortunately, only few studies on allometric biomass equations have been conducted for peat swamp forests and the results are usually not publicly accessible or well documented. Thus, the objective of this study was to develop site-specific allometric equations for above-ground biomass (AGB) estimations in tropical peat swamp forests in Indonesia. These equations were developed based on 51 destructively sampled trees. The results indicated that the developed site-specific allometric equations have coefficient of determination (R^2) greater than 95%. The R^2 values ranged from 97.0% to 98.7%, where the lowest R^2 value resulted from the simplest model which used only DBH as a predictor. Model 5, which used DBH, H and ϱ as predictive variables, provided best performance when estimating the AGB of the study area. Hence, as long as reliable data are available as input, Model 5 is recommended. The accuracy and applicability of the allometric equations for peat swamp forests could be improved further by adding more sampled trees from different tree species and/or with a wider DBH range. Considering the importance of wood density in the estimation of the AGB and the lack of this information for peat swamp forest tree species, research should be dedicated to analysing the wood density of the dominant tree species comprising the majority of the AGB density in the study area.

Keywords: Site-specific, allometric equation, above-ground biomass, peat swamp forest, Riau

ABSTRAK

Dalam kajian-kajian penaksiran biomassa hutan, pemilihan atau pengembangan persamaan-persamaan alometrik biomassa yang dapat diandalkan merupakan langkah penting yang sangat menentukan ketepatan dari dugaan biomassa yang dihasilkan. Sayangnya, hanya sedikit kajian-kajian tentang persamaan alometrik biomassa yang dilakukan di hutan rawa gambut dan hasil-hasilnya biasanya tidak dapat diakses secara umum atau terdokumentasi dengan baik. Jadi, kajian ini bertujuan untuk mengembangkan persamaan-persamaan alometrik spesifik tapak untuk pendugaan biomassa atas permukaan di hutan rawa gambut di Indonesia. Persamaan-persamaan tersebut dikembangkan berdasarkan 51 pohon contoh yang ditebang. Hasil dari kajian ini menunjukkan bahwa persamaan-persamaan alometrik yang dikembangkan mempunyai koefisien determinasi lebih dari 95% dengan rentang nilai mulai dari 97,0% sampai dengan 98,7%. Dalam hal ini, koefisien determinasi yang paling rendah dihasilkan oleh persamaan alometrik yang paling sederhana dengan satu peubah, yaitu diameter setinggi dada (Model 1). Model 5 yang menggunakan tiga peubah (diameter setinggi dada, tinggi total dan kerapatan kayu) menghasilkan dugaan biomassa atas permukaan yang paling baik di wilayah kajian. Oleh karena itu, selama data peubah tersebut tersedia, maka Model 5 direkomendasikan dalam pendugaan biomassa atas permukaan di hutan rawa gambut. Ketepatan dan penerapan dari persamaan-persamaan alometrik ini dapat ditingkatkan dengan menambahkan pohon contoh dari jenis lain dan/atau dengan rentang diameter setinggi dada yang lebih besar. Mempertimbangkan pentingnya kerapatan kayu dalam pendugaan biomassa dan kurangnya informasi ini untuk jenis-jenis pohon di hutan rawa gambut, maka penelitian perlu dilakukan untuk menganalisis kerapatan kayu untuk jenis-jenis dominan yang menyumbang kerapatan biomassa terbesar pada wilayah kajian.

Kata kunci: Spesifik tapak, persamaan alometrik, biomassa atas permukaan, hutan rawa gambut, Riau

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I. INTRODUCTION

Accurate estimation of above- and below-ground biomass (AGB and BGB) in tropical peat swamp forest ecosystems is important to understand their roles in the global carbon cycle, particularly in relation to climate change. Reliable information on the biomass ("organic material both above-ground and below-ground, and both living and dead"(FAO, 2006, p.172), expressed as oven-dry ton or Megagramme (Mg) per ha) of forest ecosystem is also crucial for assessing forest structure and condition (Chave *et al.,* 2003; Zianis, 2008; Návar, 2009), forest productivity (Clark *et al.,* 2001; Zianis, 2008) and nutrients cycle and energy fixation (Zianis *et al.,* 2005; Zianis, 2008). Biomass is also an indicator of site productivity (Návar, 2009), both in biological and economical terms (Cole and Ewel, 2006) and is important to support the implementation of sustainable forest management (Zianis *et al.,* 2005; Labrecque *et al.,* 2006; Lucas *et al.,* 2006) and the conservation of biodiversity (Lucas *et al.,* 2006).

Knowledge of the spatial distribution of and changes in the biomass has been required for some time but the need is becoming more urgent, particularly because of emerging mechanisms for mitigating greenhouse gases (GHGs), such as Reducing Emissions from Deforestation and forest Degradation (REDD) in developing countries (Gibbs *et al.,* 2007; Sierra *et al.,* 2007; Basuki *et al.,* 2009; Goetz *et al.,* 2010; Saatchi *et al.,* 2011). To best quantify carbon dynamics, consecutive measurements of forest biomass (Chambers *et al.,* 2001; Clark *et al.,* 2001) and accumulation rates (Sierra *et al.,* 2007; Návar, 2009; Wijaya *et al.,* 2010; Banskota *et al.,* 2011) are needed together with information on the extent and rate of forest disturbances associated with natural or anthropogenic land use changes and fire events (Brown *et al.,* 1995; Sierra *et al.,* 2007; Wijaya *et al.,* 2010).

Many studies on forest biomass assessment are focused on AGB (e.g. Brown, 1997; Foody *et al.,* 2001; Ketterings *et al.,* 2001; Losi *et al.,* 2003; Aboal *et al.,* 2005; Segura and Kanninen, 2005; Saatchi *et al.,* 2007; Basuki *et al.,* 2009; Kenzo *et al.,* 2009a) because it represents the largest carbon pool[2] of forest vegetation and is directly impacted by deforestation and degradation (Gibbs *et al.,* 2007). Field-based measurement is one of the methods for estimating the biomass of the forest ecosystems (Lu, 2006; Anaya *et al.,* 2009). This method is commonly conducted by applying allometric biomass regression equations or simply allometric equations (Brown, 2002; Verwer and Meer, 2010). These are mathematical equations that relate easily-measured variables (e.g. diameter at breast height, base diameter and tree height) to attributes that are more difficult to assess (e.g. standing volume and biomass or leaf area) (Ketterings *et al.,* 2001; Goetz *et al.,* 2010).

Many allometric equations have been developed for tropical forests, with some being site-specific and developed from in situ harvesting of sampled trees of mixed-species (e.g. Yamakura *et al.,* 1986; Chambers *et al.,* 2001; Ketterings *et al.,* 2001; Segura and Kanninen, 2005; Jepsen, 2006; Basuki *et al.,* 2009; Kenzo *et al.,* 2009a; Kenzo *et al.,* 2009b). Others (e.g. Brown *et al.,* 1989; Brown, 1997; Zianis and Mencuccini, 2004; Chave *et al.,* 2005; Pilli *et al.,* 2006) are more generalized having been developed from trees sampled across a wider geographical range and as a function of forest type. Well-known and commonly used equations include that of Brown (1997), which was derived from sampled trees collected across the pan-tropical region, and Chave *et al.*, (2005), which considered the differences between dry and wet forest types. These equations have used data from the Neotropics, Southeast Asia and Oceania, including Indonesia, but none of the sampled trees have been collected from peat swamp forests (Verwer and Meer, 2010). The use of allometric equations is advocated as direct field measurement, whilst it is more accurate (Lu, 2006), but it is also expensive, time

[2] In peat swamp forests, the AGB represents the second largest carbon pool after peat soil.

consuming and labour intensive (Houghton, 2005).

Compared to other tropical forest ecosystems, peat swamp forest is considered a unique and fragile ecosystem (Page *et al.,* 1999; Rieley, 2007). It is characterized by its occurrence on peat soil with high-rainfall, high-temperature, waterlogged and acidified substrate conditions that lack oxygen (Wösten *et al.,* 2006; Hirano *et al.,* 2007; Jaenicke *et al.,* 2008; Posa *et al.,* 2011) where the decomposition rate of woody plant debris is slower than the accumulation rate of the materials (Maltby and Immirzi, 1993; Rieley and Page, 2005). This ecosystem is fragile because of the strong interdependency between hydrology, ecology and landscape morphology (Page *et al.,* 1999) where a change in any of these components will alter and affect the balance of the ecosystem (Hooijer *et al.,* 2009; Hooijer *et al.,* 2010). As a consequence of this characteristic, peat swamp forest ecosystem has the potential to store huge amounts of carbon (Sorensen, 1993; Tawaraya *et al.,* 2003; Jaenicke *et al.,* 2008), especially as Soil Organic Matter (SOM) (Hirano *et al.,* 2007).

Although peat swamp forest is a significant repository of carbon, disturbance can transform it to a large source of carbon emissions (Rieley and Page, 2005). However, there is a lack of information on the amount of the biomass stored within the peat swamp forest (Verwer and Meer, 2010). The majority of studies have focused mainly on the impacts of fire and subsequent recovery of the forest ecosystem, the amount of carbon in the peat soils, mycorrhizal activity, and biodiversity (Page *et al.,* 2002; Tawaraya *et al.,* 2003; Wahyunto *et al.,* 2003; Wahyunto *et al.,* 2004; Wahyunto *et al.,* 2005; Hooijer *et al.,* 2006; Wahyunto *et al.,* 2006; Wösten *et al.,* 2006; Jaenicke *et al.,* 2008; Uryu *et al.,* 2008; Wahyunto and Suryadiputra, 2008; Wösten *et al.,* 2008; Wahyunto *et al.,* 2010). Few studies have been conducted on the biomass of the peat swamp forests (e.g. Ludang and Jaya, 2007; Krisnawati and Imanuddin, 2011; Tan *et al.,* 2011) and most have used the available generalized or pan-tropical allometric equations (e.g. Brown *et al.,* 1989; Brown, 1997; Chave *et al.,* 2005) instead of allometric equations specific to peat swamp forests and from Indonesia. Currently, site-specific allometric equations for peat swamp forest that are publicly available are limited (see Solichin *et al.,* 2011; Krisnawati *et al.,* 2012). Thus, the objective of this study was to develop site-specific allometric equations for AGB estimations for tropical peat swamp forests, with special reference to peat swamp forests in Rokan Hilir District, Riau Province.

II. MATERIAL AND METHOD

A. Study Site

This study was conducted at the selected logging blocks within the concession area

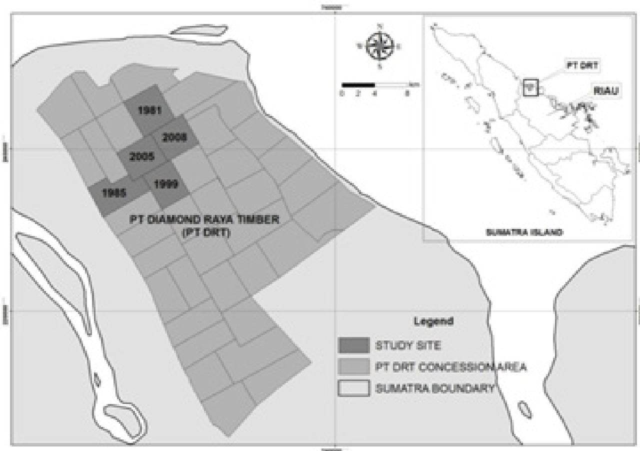

Figure 1. The selected study site within the forest concession area of PT. Diamond Raya Timber

managed by PT. Diamond Raya Timber (PT. DRT) (Figure 1) in Rokan Hilir District, Riau Province, Indonesia (100°48' – 101°13' E and 1°49' – 2°18' N (Istomo, 2002). It is mainly covered by the lowland peat swamp forest with the dominant commercial species of balam (*Palaquium obovatum* (Griffith) Enql.), meranti batu (*Shorea uliginosa* Foxw.), ramin (*Gonystylus bancanus* (Miq.) Kurz.), and terentang (*Camnosperma coriaceum* (Jack.) Hallier f. ex v. Steenis). This forest is also the important habitat for the endangered species of the Sumatran tiger (*Panthera tigris sumatrae*).

The topography of the area is flat with the elevation ranges from 0-8 m a.s.l. (meter above sea level). In addition, the area is geologically dominated by peat dome along with alluvial and marine groups (Istomo, 2002). The dominant soil type is thick peat soil with a depth of more than 3 m, while the minor ones are gley, alluvial and podzolic. Based on the Schmidt and Ferguson climate classification, the area is classified as A type with Q value of 10.1% (Istomo, 2002). The average monthly rainfall ranges from 51.3 to 301.6 mm where the highest is in November (301.6 mm) and the lowest is in March (51.3 mm). Furthermore, the mean annual temperature ranges from 25 to 27 °C and the relative humidity ranges from 79% to 90%.

B. Data Collection

The data collection through destructive sampling was carried out from August to September 2008. A total of fifty one healthy[3] trees comprising eleven species with the DBH ranging from 5.2 to 62.7 cm were felled (details are presented in Appendix 1). The sampled trees were mainly selected based on dominant tree species present in the study area according to the available data from the permanent sample plot (PSP). Out of the eleven tree species felled during the fieldwork, nine were associated with the dominant species. The DBH, which is the diameter at 1.3 m above the ground or 30 cm above the buttress (FAO, 2004), was measured using a diameter tape before the tree was felled. The scientific name of the sample trees were verified using the database of the World Agroforestry Centre (CGIAR, 2008) and a previous study (Istomo, 2002).

After the tree was felled, the total tree height (H) was measured using a 50-m measuring tape. Then, the sample tree was separated into four components: (1) leaves, (2) twigs (diameter < 3.2 cm), (3) small branches (diameter between 6.4 cm and 3.2 cm), and (4) large branches and stems (diameter > 6.4 cm) following the procedure used by Kettering *et al.*, (2001). All of these components were weighed directly in the field to obtain their fresh weight using a portable hanging balance with 100-kg capacity.

The subsamples for each component were collected from each sampled tree for oven-dry weight analysis. Depending on the DBH, three subsamples (with a minimum weight of 100 g for each subsample) were collected for each component. For large branches and stems, small branches and twigs, the subsamples were collected from the lower, middle and upper part of the tree for each component pool, whereas for leaves, the subsamples were taken from the total amount of the leaves taken from the tree. These subsamples were weighed in the field to obtain their fresh weight using a small balance with 2-kg capacity and stored in sealed plastic bags such that moisture was retained before sending them to the laboratory. A total of 592 subsamples from 51 sampled trees were sent to the Soil Science Laboratory of the Faculty of Agriculture in Sebelas Maret University (UNS), located in Surakarta, Central Java of Indonesia, for oven dry weight analysis. The wood and leave subsamples were oven-dried at 105°C until a relatively constant weight was obtained (Nelson *et al.,* 1999; Ketterings *et al.,* 2001). The total dry weight or Dry Matter (DM) of the stems were calculated using equation (1) (Jayaraman, 1999).

$$TDW_{stem} = \frac{TDW_{samples}}{TFW_{samples}} \times TFW_{stem} \qquad (1)$$

[3] Healthy tree in this article is defined as a tree without broken top or infected by a disease.

where TDW_{stem} is the total dry weight of the stems, $TDW_{samples}$ is the total dry weight of the stems' subsamples, $TFW_{samples}$ is the total fresh weight of the stems' subsamples and TFW_{stem} is the total fresh weight of the stems. In addition, the stump height (l) and diameter (D_{stump}) were measured to estimate its volume using a cylinder volume formula as in equation (2), while its dry weight were estimated by multiplying its volume with the wood density of the stem (ϱ) (Ketterings *et al.,* 2001).

$$V_{stump} = \frac{\pi (D_{stump})^2 l}{4} \qquad (2)$$

where V_{stump} is the stump volume, π is a constant value (3.142), D_{stump} is the stump diameter and l is the stump height/length. Similarly, the total dry weight for all other components of the tree was calculated based on equation (1) by taking into account the total dry weight of the subsamples of the components, the total fresh weight of components' subsamples and the total fresh weight of the components. Moreover, the total dry weight of the sampled tree was calculated as the sum of the dry weight of its components and stump. This refers to the above-ground biomass of the tree (AGB_{tree}). Furthermore, data on DBH and H from destructive sampling and ϱ data from the database of the World Agroforestry Centre (CGIAR, 2008), which are available online, were used to develop site-specific allometric equations.

C. Data Analysis

1. Regression models

Three types of regression models were used to develop the biomass equations: (1) Type I was developed using DBH (AGB_{tree} – D model), (2) Type II was developed using DBH and H (AGB_{tree} – D – H model), and (3) Type III was developed using DBH, H and ϱ (AGB_{tree} – D – H – ϱ). Details of these models are presented in Table 1. The data analysis for constructing the models was carried out using the SPSS® 14.0 statistical package (SPSS Inc., 2005).

2. Model selection

The model selection was based on six statistical parameters, of which five are explained by Parresol (1999): (1) fit index (*FI*), (2) standard error of estimate in actual unit (Se), (3) coefficient of variation (*CV*) in percent, (4) Furnival's index (*I*), and (5) corrected mean percent standard error of prediction (($\overline{S}$ (%)) or average (unsigned) deviation (Nelson *et al.,* 1999; Basuki *et al.,* 2009). The sixth parameter is the Akaike's Information Criterion/*AIC* (Akaike, 1974) calculated using equation (3). The best model will have the lowest *AIC* value. where *AIC* is the Akaike's Information

Table 1. Type of allometric equation models for AGB estimation

Type	Allometric equation	Model
I.	$AGB_{tree} = exp\ (a + b \times In\ (D))$	1
II.	$AGB_{tree} = exp\ (a + b \times In\ (D^2H))$	2
	$AGB_{tree} = exp\ (a + b \times In\ (D) + C \times In\ (H))$	4
III.	$AGB_{tree} = exp\ (a + b \times In\ (D^2H\tilde{n})$	3
	$AGB_{tree} = exp\ (a + b \times In\ (D) + c \times In\ (H) + d \times In\ (\tilde{n}))$	5

Notes: AGB_{tree} is the above-ground biomass per tree (kg DM $tree^{-1}$), exp is *e* raise to the power of, ln is natural logarithm, *D* is the diameter at breast height (cm), *H* is the total tree height (m), ϱ is the wood density or the wood specific gravity (g cm^{-3}), and *a, b, c,* and *d* are the regression coefficients

$$AIC = C\ln\left(\frac{S_e}{C}\right) + 2p^* \text{.....................................(3)}$$

Criterion, C is the number of observed data, ln is natural logarithm, SS_e is the residual sum of squares, and p^* is the number of parameters or coefficient in the models, including intercept.

3. Model prediction

During the analysis, the field data were transformed based on natural logarithm. This process introduced a systematic bias of the biomass estimates when they were back-transformed to the actual unit, whereby the biomass estimates were usually an underestimate of the actual biomass (Chave *et al.,* 2005). For this reason, biomass estimates should be multiplied by a correction factor (*CF*), which is a number close to 1. In this study, the biomass estimates were corrected using equation (4) from Snowdon (1991).

$$CF_{SD} = \left(\frac{\frac{\sum_{i=1}^{n} Y_i}{n}}{\frac{\sum_{i=1}^{n} \hat{Y}_i}{n}}\right) \text{.....................................(4)}$$

where CF_{SD} is the correction factor described by Snowdon (1991), Y_i is the observed data of the i^{th} sample, $\hat{Y}_i$ is the estimated data of the i^{th} sample, and *n* is the number of sample.

III. RESULT AND DISCUSSION

A. Result

All the regression models were statistically highly significant ($p < 0.0001$) and generally fitted the data well. The residuals for AGB models were relatively normally distributed and did not show any pattern (Appendix 2). The regression coefficient and the statistical summary for each model are presented in Table 2. Based on the model summary, Model 3 and 5, which used DBH, H and ϱ, performed better in estimating AGB. This was indicated by the higher R^2 and adjusted R^2 and the lower SEE and MSE. Between Model 3 and 5, Model 5 (which uses three single-variables), performed better than the combined variable of Model 3. There was no difference in statistical summaries between Model 2 and 4 in relation to the type of variable used. Model 1, which is the simplest model, gave the lowest performance. However, in general, all the models had acceptable goodness-of-fit to the data indicated by R^2 which was greater than 0.95.

When using only DBH as a predictive variable (Model 1), 97% of the variation of the AGB (Table 2) was explained. Adding *H* as a second predictor improved the performance of the model by increasing R^2 and adjusted R^2 and subsequently reducing *SEE* and *MSE*. Since the R^2 for Model 1 was already high, adding H has only slightly increased the R^2. For combined variable (Model 2), R^2 has increased relatively by 1.1%, while *SEE* was reduced relatively by 19.8%. Adding ϱ to the model as the third predictor has slightly improved the performance of the models. As a combined variable (Model 3 to Model 2), ϱ improved the R^2 by 0.4% and reduced the *SEE* by 11.2%. As an independent variable (Model 5 to Model 4), ϱ increased the R^2 by 0.6% and decreased the *SEE* by 15.0%.

The model selection was based on the comparison parameters explained by Parresol (1999) and is summarised in Table 3. Based on these parameters, Model 5, which used three independent variables, outperformed all other models, which is indicated by the highest *FI* value and the lowest S_e, CV, I, $\bar{S}$ *(%)*, and AIC values. Adding *H* to the DBH reduced the Se up to ~50 kg, the *CV* (as a measure of dispersion around the mean) up to ~6% and the $\bar{S}$ *(%)* (as a measure of precision) up to ~4% (non-corrected models). Based on the comparison parameters in Table 3, Model 2 performed slightly better in estimating AGB in the study area, which previously could not be observed from the statistical summary of the models in Table 2. Adding the H and ϱ together to the DBH in the AGB models reduced the Se up to

Table 2. Regression coefficients and statistical summary for each AGB model

Model	Coefficient			Model Summary			
	Symbol	Value	*SE*	R^2	Adjusted R^2	*SEE*	*MSE*
1.	*a*	-2.551	0.208	0.970	0.969	0.333	0.111
	b	2.660	0.067				
2.	*a*	-3.398	0.182	0.981	0.980	0.267	0.071
	b	0.995	0.020				
3.	*a*	-2.965	0.154	0.985	0.984	0.237	0.056
	b	0.990	0.018				
4.	*a*	-3.580	0.256	0.981	0.980	0.267	0.071
	b	1.827	0.166				
	c	1.229	0.232				
5.	*a*	-3.126	0.240	0.987	0.986	0.227	0.051
	b	2.011	0.147				
	c	0.966	0.206				
	d	0.641	0.145				

Notes: SE = standard error of the coefficient, R^2 = coefficient of determination, *SEE* = standard error of the estimate and *MSE* = mean square error. All models and coefficients are statistically significant at $\alpha = 0.05$ (p <0.0001, except for coefficient *d* in Model 5: $p = 0.001$)

Table 3. A summary of comparison parameters of the developed models for AGB estimation

Model	Comparison parameters							*CF*
	FI	*Se*	*CV*	*I*	$\bar{S}$ (%)	*AIC*	Bias	
1	0.91	337.90	40.59	84.79	25.97	595.88	-19.74	NC
	0.91	339.84	40.82	84.79	26.63	596.47	0.00	1.024[a]
2	0.93	288.09	34.60	67.99	22.21	579.61	-22.32	NC
	0.93	287.41	34.52	67.99	22.51	579.37	0.00	1.028[a]
3	0.93	283.79	34.09	60.35	20.71	578.08	-15.47	NC
	0.93	285.99	34.35	60.35	21.07	578.87	0.00	1.019[a]
4	0.93	288.32	34.63	67.99	22.10	580.64	-23.68	NC
	0.93	286.92	34.46	67.99	22.41	580.15	0.00	1.029[a]
5	0.96	233.52	28.05	57.80	19.32	560.07	-17.42	NC
	0.96	232.94	27.98	57.80	19.52	559.82	0.00	1.021[a]

Notes: *FI* = Fit Index, S_e = Standard error in actual unit, *CV* = Coefficient of Variation, *I* = Furnival's index, $\bar{S}$ *(%)* = Average deviation, *AIC* = Akaike's Information Criterion, *NC* = Not Corrected, a = corrected using formula from Snowdon (1991)

~104 kg, the *CV* up to ~12% and the $\bar{S}$ (%) up to ~7% (non-corrected models). In this case, Model 5 (which uses three single predictors) performed better than Model 3 (which uses a compound of three variables). Adding extra variables into the models increased the *FI* values up to 5%.

Log-transformation of the datasets during the model construction resulted in the underestimation of the actual biomass as indicated by the negative values of the bias (Table 3). The underestimation of actual biomass was also observed using a scatter plot of predicted AGB against observed AGB as presented in Appendix 3. Multiplying the predicted biomass by a *CF* was intended to remove the systematic bias due to back-transformation. In this study, the formula of Snowdon (1991) was used.

Table 4. Mean average deviation ($\bar{S}$ (%)) per DBH class for each model

Model	Mean $\bar{S}$ (%)			
	DBH<= 10 cm	10 cm <DBH<= 30 cm	30 cm<DBH<= 50 cm	DBH> 50 cm
1	29.10	28.26	21.15	30.49
2	25.75	22.77	19.18	23.53
3	22.87	22.92	18.31	18.80
4	26.44	22.34	18.82	23.53
5	21.79	20.79	16.60	18.49

Furthermore, regardless of use, the CF did not necessarily improve the performance of the models in total (Table 3), as evaluated from the increased values of S_e, *CV*, $\bar{S}$ *(%)*, and *AIC*. However, the *CF* formula from Snowdon (1991) was useful in removing the bias of the models.

This study was conducted in peat swamp forests that have been actively logged by a commercial company. Following the current silvicultural system, the company is extracting the commercial tree species with a minimum DBH of 30 cm (Istomo *et al.*, 2010). Therefore, it is important to evaluate the $\bar{S}$ *(%)* based on the DBH classes. This information is useful in selecting the model for the biomass study in relation to the forest condition, especially the distribution of the diameters. The developed models have generally low $\bar{S}$ *(%)* of AGB (< 30%; Table 4). The exception was Model 1 with a DBH greater than 50 cm (30.5%). All of the equations tended to have a higher $\bar{S}$ *(%)* when the smaller DBH classes were considered. For DBH class less than 10 cm, the $\bar{S}$ (%) ranged from 21.8% to 29.1%, while for DBH class 10-30 cm, the $\bar{S}$ *(%)* ranged from 20.8% to 28.3%. This $\bar{S}$ *(%)* decreased with larger DBH classes giving common values of less than 20%, except for Model 1 (30.5% at DBH > 50 cm). In general, Model 5 provided the most precise estimate of AGB in the study area, as indicated by the smallest values of $\bar{S}$ *(%)* in all DBH classes. The visualization of the $\bar{S}$ *(%)* based on the DBH classes is presented in Figure 2.

B. Discussion

1. Allometric equations

The selection or development of reliable allometric biomass equations is an essential step in estimating the AGB of the forest (Crow,

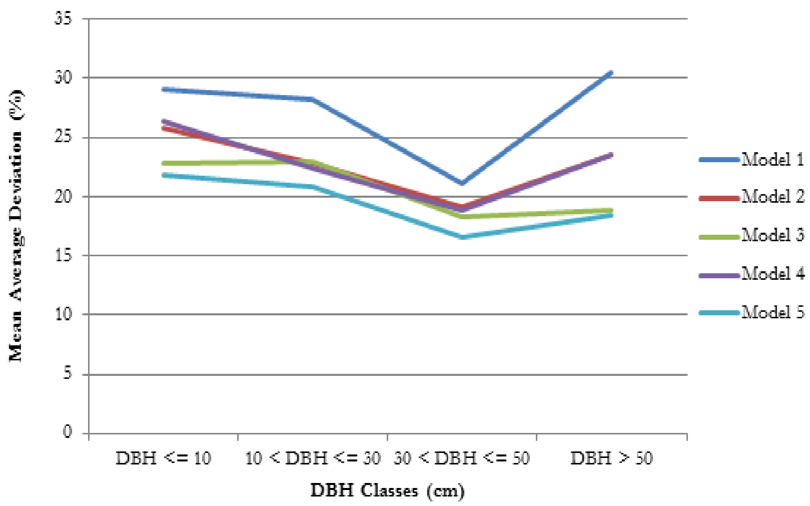

Figure 2. The mean average deviation ($\bar{S}$ (%)) based on DBH classes for each allometric model

1978; Cunia, 1987; Brown *et al*., 1989; Chave *et al*., 2001; Houghton *et al*., 2001; Chave *et al*., 2004; Chave *et al*., 2005). The basic idea of developing allometric equation is to estimate the difficult-to-measure tree characteristics (e.g. biomass) from one that is relatively easy to measure such as DBH (Goetz *et al*., 2010). Chave *et al*. (2004) pointed out that the most important source of error in forest biomass studies is the incorrect or inappropriate choice of allometric equation. Species-specific allometric equations, which are commonly used in the biomass study of temperate forest (e.g. Ter-Mikaelian and Korzukhin, 1997; Jenkins *et al*., 2003; Zianis *et al*., 2005), are not applicable to tropical forest which has high number of species per ha. In this case, the mixed-species allometric equations are more suitable (Ketterings *et al*., 2001; Chave *et al*., 2005).

Many studies have been conducted to develop mixed-species allometric equation for biomass estimation in tropical forest (e.g. Brown *et al*., 1989; Brown *et al*., 1995; Brown, 1997; Araujo *et al*., 1999; Nelson *et al*., 1999; Chambers *et al*., 2001; Chave *et al*., 2001; Ketterings *et al*., 2001; Chave *et al*., 2005; Nogueira *et al*., 2008b; Basuki *et al*., 2009; Kenzo *et al*., 2009a; Kenzo *et al*., 2009b). However, few studies on allometric biomass equations have been conducted for peat swamp forests and the results are usually not publicly accessible (Verwer and Meer, 2010; Solichin *et al*., 2011). Therefore, it is expected that this study will contribute significantly to the improvement of biomass and carbon estimation accuracies in peat swamp forests.

DBH as a variable has been found to have a strong correlation with biomass (with R^2 typically more than 95%). Previous studies recommended the application of the allometric equation which uses only DBH, although largely for practical reason (e.g. Brown, 1997; Basuki *et al*., 2009; Návar, 2009). This is because the DBH is more easily measured in the forest and collected during the regular forest inventory (Segura and Kanninen, 2005). In this study, allometric equation with only DBH as a predictor (Model 1) had an R^2 of 97.0%. The $\overline{S}$ *(%)* value was 26.6% which is comparable with the $\overline{S}$ *(%)* of the DBH-only model in mixed-dipterocarp forest in East Kalimantan (Basuki *et al*., 2009). This statistic indicates the average size of error as a percent of the mean and can be used as a precision indicator (Parresol, 1999), where the lower the value the higher the precision. Although the DBH-only model is more practical, the model tends largely to underestimate or overestimate the actual biomass. For example, *Parastemon urophyllum* and *Palaquium obovatum* with the same DBH of 7.6 cm have weights of 35.15 kg and 8.94 kg, respectively. Using only DBH as a predictive variable, Model 1 estimated AGB for these two tree species to be 17.6 kg. As a result, the $\overline{S}$ (%) for *P. obovatum* was very large (96.8%), and almost twice than the $\overline{S}$ *(%)* for *P. urophyllum* (49.9%). This is because the architecture of the tree is not accounted in the model (i.e. the H differs being 11.52 m and 7.83 m, respectively). For trees with larger DBH, the $\overline{S}$ *(%)* is relatively lower but the actual residual is large. Therefore, adding H as a second predictor in the model is important.

Numerous other studies on forest biomass (e.g. Crow, 1978; Nelson *et al*., 1999; Ketterings *et al*., 2001; Chave *et al*., 2005; Cole and Ewel, 2006; Fehrmann and Kleinn, 2006; Wang, 2006) have previously noted that adding H can improve the model performance. Adding H to DBH in the AGB models increases the R^2 by up to 1.7% relative to Model 1. Although adding H can only marginally increase the $R^{2,}$ the *SEE* was reduced significantly (up to 22%). In addition, the Se was reduced as well as the *CV* and the $\overline{S}$ *(%)*. Using Model 2, the estimated biomass values for *P. urophyllum* and *P. obovatum* were 22.13 kg and 15.07 kg, respectively. The $\overline{S}$ *(%)* was reduced to 68.5% (-28.3%) and 37.0% (-12.9%), respectively.

Model 4, which considers H as an independent variable, provided a better estimate. The estimated biomass values for *P. urophyllum* and *P. obovatum* were 14.64 kg and 23.52 kg, respectively and the $\overline{S}$ *(%)* values were 63.7% and 33.1%, respectively. The advantage of adding H was more evident for larger trees. For example, *Ilex macrophylla* and *Gonystylus bancanus* have the same DBH (40.0 cm) but their *H* and AGB_{tree} were different, with these being 24.14 m and 30.21 m, and 1186.95 kg and 1779.28 kg, respectively. The estimated AGB_{tree} using Model 1 gave 1458.87 kg for both tree species and the $\bar{S}$ (%) values were 22.9% and 18.0%, respectively. When Model 4 was used to estimate the biomass of these trees, the $\bar{S}$ *(%)* values for *I. macrophylla* and *G. bancanus* became 2.2% and 10.1%, respectively.

Further improvement can be achieved by adding ϱ to the model. The ϱ is an important tree parameter in estimating biomass, in particular for larger trees (Baker *et al*., 2004; Chave *et al*., 2005; Nogueira *et al*., 2008a). This study found that allometric equation which uses three independent variables (i.e. DBH, *H* and ϱ) gave the best performance (Model 5) and supports previous studies (e.g. Nelson *et al*., 1999; Chave *et al*., 2005). Incorporating ϱ into the DBH-*H* models increased the R^2 by less than 1% but reduced the relative *SEE* by up to ~15%. Adding H and ϱ together to DBH increased the performances of the model significantly based on the comparison parameters. However, for some tree species, the ϱ was not an important parameter. For example, *Shorea uliginosa* and *P. urophyllum* have the same DBH of 43.70 cm and relatively the same *H* (33.30 m and 33.46 m) and also dry weight biomass (2300.50 kg and 2392.44 kg), but their ϱ values were different (0.640 g cm^{-3} and 1.040 g cm^{-3}). In this case, the most important factor was the difference in canopy structure (branching system). *S. uliginosa* tends to have a heavier canopy with more branches and bigger leaves compared to *P. urophyllum*. Thus, although *P. urophyllum* has significantly higher ϱ, the dry weight biomass values were not largely different. For these species, Model 5, which uses three independent variables, resulted in lower precision than Model 4, which uses two independent variables (without ϱ). The $\bar{S}$ *(%)* values were 13.9% and 13.6% (Model 5) and 7.9% and 10.9% (Model 4). Basuki *et al.* (2009) found that ϱ is not statistically significant for *Dipterocarpus*, *Hopea* and *Shorea* in East Kalimantan. Nelson *et al.* (1999) also found that ϱ is not significant for *Bellucia* species in the central Amazon.

The results of the model comparison indicated that increasing number of parameters or independent variables increases the performance of the model. However, it is important to note that including more variables in the model increases the regression error or uncertainty of the biomass through error propagation (Chave *et al*., 2004; Chave *et al*., 2005). In addition, information on species-specific ϱ for peat swamp forest species is not always available in the database of the World Agroforestry Centre (CGIAR, 2008), although the average value of the wood density for the genus can be used instead (Krisnawati *et al*., 2012), and H is usually not collected during the forest inventory (Chave *et al*., 2005). An alternative way to acquire *H* information is by constructing a stand-specific allometric relationship between *H* with DBH from destructively sampled trees and then using the developed equation to predict the *H* for the rest of the trees being studied (Brown *et al*., 1989; Chave *et al*., 2005), although errors in this relationship need to be accounted for. Adding *H* can improve the model's performance, but *H* is rarely used in practice because of two reasons: (1) measuring *H* in a forest ecosystem, particularly in dense tropical forests is much more difficult and time consuming but less accurately estimated than DBH (Gower *et al*., 1999); and (2) adding *H* into the model increases the regression error in the biomass estimate (Chave *et al*., 2005).

2. The applicability of the developed site-specific allometric equations

The developed models are considered as the site-specific allometric equations for the study area as the sampled trees that were used to construct the model were harvested *in situ*. The models should be used in the biomass studies of peat swamp forests within their DBH range (5.2-62.7 cm). It is important to consider the DBH range in applying allometric equations as the error tends to increase with increases in

DBH. Applying allometric equations outside the DBH range will result in bigger errors, especially for the larger trees.

3. The limitations of the developed site-specific allometric equations

There are several limitations in developing site-specific allometric models for AGB in this study. Firstly, during the oven-dry weight analysis, the sub-subsampled tree components were used instead of the subsampled ones. Pre-analysis was carried out to find the moisture differences between field fresh weight and laboratory fresh weight using 44 randomly selected subsampled tree components (stems, branches, twigs, and leaves). The average percent differences were 2.8%, 4.0%, 4.9%, and 5.9% for stems, branches, twigs and leaves, respectively. The correction for each component was conducted by adding the lower value of confidence interval in paired samples t-test as suggested by Statistical Consulting Unit at the Australian National University, with these being 7.60 g, 6.86 g, 7.02 g, and 6.58 g for stems, branches, twigs, and leaves, respectively. This correction may introduce a systematic bias in the predicted biomass.

Secondly, this study used a limited number of species for constructing the allometric models (11 species in total with nine dominant species) within a relatively narrow DBH range (i.e. 5.2-62.7 cm). Based on the plot measurement during the field campaign, approximately 53 tree species have been identified (mostly by their local name) and four species were unknown. Considering the number of sampled tree species across the DBH range, the models may not well represent the peat swamp forest at large (Chave *et al*., 2005). Third, the tree species were recorded by their local names and because there are different local names for the same species and different species with the same local name, identifying the correct scientific name in the literature or database can lead to misidentification. Furthermore, this can lead to an incorrect use of ϱ estimates from the database.

IV. CONCLUSION

In this study five site-specific allometric equations have been developed based on destructively sampled trees. Model 5, which used DBH, H and ϱ as predictive variables, has the best performance in estimating the AGB of the study area. As long as reliable data are available for those variables, the application of Model 5 is recommended in estimating the AGB of peat swamp forests. However, when reliable data on H and ϱ are unavailable, the simplest model that uses only DBH as a predictor (Model 1) can be applied. The accuracy and applicability of the site-specific allometric equations could be improved further by adding more sampled trees from different tree species and/or with a wider DBH range. Considering the importance of wood density in AGB estimation and the lack of this information for peat swamp forest tree species, research should be dedicated to analysing the wood density of the dominant tree species comprising the majority of the AGB density in the study area. In addition, it is important to test the models at other sites (peat swamp forest at different locations). Combining the dataset from a wide-range of geographical area may improve the generic applicability of the models.

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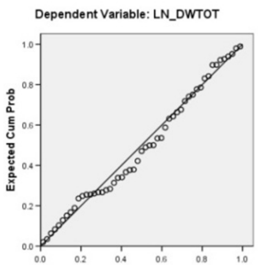
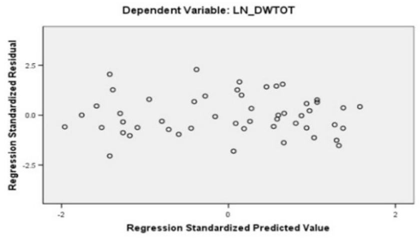
APPENDIX 1. Sampled trees destructively collected to develop site-specific allometric equations for AGB estimation in tropical peat swamp forests

ID	Tree species		DBH	*H*
	Local name	**Scientific name**	**(cm)**	**(m)**
1	Terentang	*Campnosperma coriaceum* (Jack.) Hallier f. ex v. Steenis	9.6	10.3
2	Terentang	*Campnosperma coriaceum* (Jack.) Hallier f. ex v. Steenis	15.1	12.4
3	Terentang	*Campnosperma coriaceum* (Jack.) Hallier f. ex v. Steenis	21.6	12.2
4	Terentang	*Campnosperma coriaceum* (Jack.) Hallier f. ex v. Steenis	31.5	23.5
5	Terentang	*Campnosperma coriaceum* (Jack.) Hallier f. ex v. Steenis	42.6	32.1
6	Terentang	*Campnosperma coriaceum* (Jack.) Hallier f. ex v. Steenis	52.5	34.3
7	Kelat	*Carallia brachiata* (Lour.) Merr.	8.3	10.0
8	Jambu-jambu	*Eugenia* sp.L.	7.8	10.3
9	Jambu-jambu	*Eugenia* sp.L.	15.5	13.8
10	Jambu-jambu	*Eugenia* sp.L.	22.3	19.8
11	Jambu-jambu	*Eugenia* sp.L.	33.1	17.9
12	Manggis-manggis	*Garcinia celebica* (Burm.) L.	6.0	6.9
13	Manggis-manggis	*Garcinia celebica* (Burm.) L.	18.5	17.1
14	Manggis-manggis	*Garcinia celebica* (Burm.) L.	25.1	18.7
15	Manggis-manggis	*Garcinia celebica* (Burm.) L.	31.2	21.5
16	Ramin	*Gonystylus bancanus* (Miq.) Kurz.	5.2	8.1
17	Ramin	*Gonystylus bancanus* (Miq.) Kurz.	11.8	15.5
18	Ramin	*Gonystylus bancanus* (Miq.) Kurz.	24.8	22.4
19	Ramin	*Gonystylus bancanus* (Miq.) Kurz.	38.3	30.7
20	Ramin	*Gonystylus bancanus* (Miq.) Kurz.	40.0	30.2
21	Ramin	*Gonystylus bancanus* (Miq.) Kurz.	62.7	39.4
22	Darah-darah	*Horsfieldia glabra* (Blume) Warb.	7.1	9.3
23	Darah-darah	*Horsfieldia glabra* (Blume) Warb.	8.5	7.5
24	Darah-darah	*Horsfieldia glabra* (Blume) Warb.	13.6	13.8
25	Darah-darah	*Horsfieldia glabra* (Blume) Warb.	23.6	22.5
26	Darah-darah	*Horsfieldia glabra* (Blume) Warb.	33.0	23.9
27	Pasir-pasir	*Ilex macrophylla* Hook. F.	6.8	8.7
28	Pasir-pasir	*Ilex macrophylla* Hook. F.	10.6	12.5
29	Pasir-pasir	*Ilex macrophylla* Hook. F.	22.0	16.6
30	Pasir-pasir	*Ilex macrophylla* Hook. F.	36.5	24.5
31	Pasir-pasir	*Ilex macrophylla* Hook. F.	40.0	24.1
32	Pasir-pasir	*Ilex macrophylla* Hook. F.	54.4	27.9
33	Balam	*Palaquium obovatum* (Griffith) Engl.	7.6	7.8
34	Balam	*Palaquium obovatum* (Griffith) Engl.	17.0	17.2
35	Balam	*Palaquium obovatum* (Griffith) Engl.	28.5	24.8
36	Balam	*Palaquium obovatum* (Griffith) Engl.	30.3	23.2
37	Balam	*Palaquium obovatum* (Griffith) Engl.	41.0	29.1
38	Balam	*Palaquium obovatum* (Griffith) Engl.	51.5	28.1
39	Milas	*Parastemon urophyllum* (Wallich. ex A. DC) A.DC	7.6	11.5
40	Milas	*Parastemon urophyllum* (Wallich. ex A. DC) A.DC	15.8	20.0
41	Milas	*Parastemon urophyllum* (Wallich. ex A. DC) A.DC	23.1	26.4
42	Milas	*Parastemon urophyllum* (Wallich. ex A. DC) A.DC	32.7	28.8
43	Milas	*Parastemon urophyllum* (Wallich. ex A. DC) A.DC	43.7	33.5
44	Milas	*Parastemon urophyllum* (Wallich. ex A. DC) A.DC	54.5	33.2
45	Meranti bunga	*Shorea teysmanniana* Dyer ex Brandis	9.0	9.8
46	Meranti batu	*Shorea uliginosa* Foxw.	8.5	6.4
47	Meranti batu	*Shorea uliginosa* Foxw.	12.5	12.8
48	Meranti batu	*Shorea uliginosa* Foxw.	22.7	25.0
49	Meranti batu	*Shorea uliginosa* Foxw.	31.0	28.8
50	Meranti batu	*Shorea uliginosa* Foxw.	43.7	33.3
51	Meranti batu	*Shorea uliginosa* Foxw.	50.7	33.3

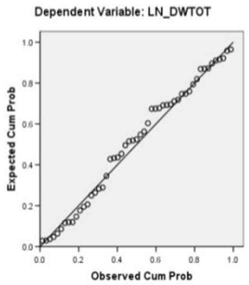
APPENDIX 2. Normal P-P Plot of regression standardized residual and scatterplot of regression standardized predicted value against regression standardized residual for each model: (a) Model 1, (b) Model 2, (c) Model 3, (d) Model 4, and (e) Model 5

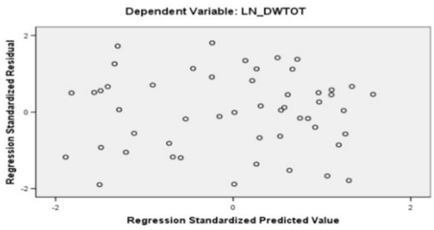
(a)



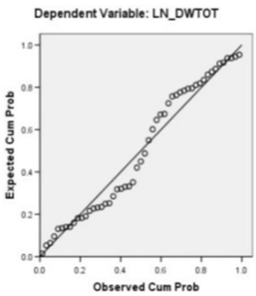


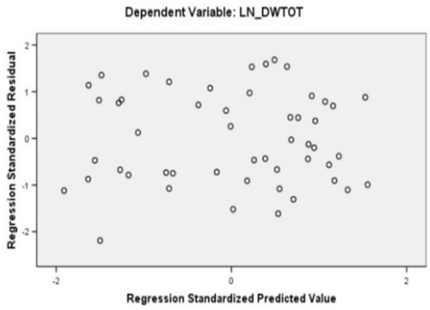
(b)



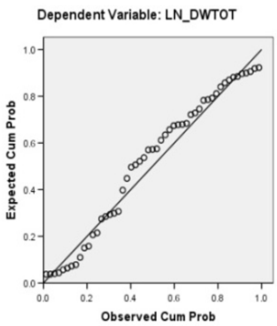


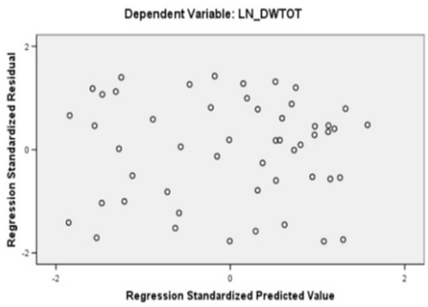
(c)



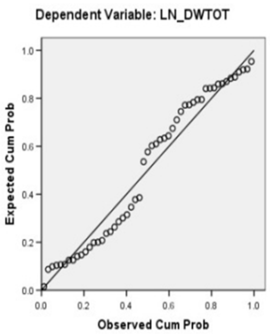


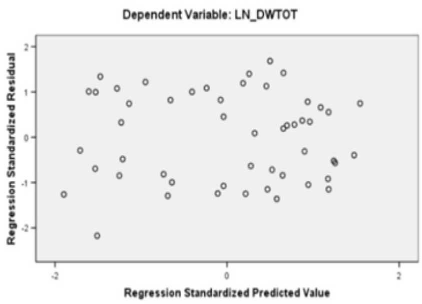
(d)





(e)





APPENDIX 3. Scatterplots of predicted AGB against observed AGB for each model without correction (left hand side) and with correction using Snowdon's formula (right hand side): (a) Model 1, (b) Model 2, (c) Model 3, (d) Model 4, and (e) Model 5.

(a)

(b)

(c)

(d)

(e)