ABOVEGROUND BIOMASS ASSESSMENT OF DEGRADED RAINFOREST USING IKONOS-2: SPECIFIC FOREST CLUSTER ANALYSIS

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ABSTRACT: Accurate estimation of aboveground biomass (AGB) has increasingly important especially dealing with various levels of forest degradation. Exploration of forest texture and forest structure helps to define forest type which shaping a distribution of AGB. In this study, high resolution satellite imagery of IKONOS-2 was used to assess the AGB of tropical Borneo rainforest at specific degradation level. Study site consists of degraded lowland Dipterocarp forest located at Tangkulap forest reserves in Sabah. The satellite image was segmented using eCognition and classified into three specific levels of forest cluster that are early, mid and late-successional forest. Field plots were assigned to the cluster by AGB to reflect the degradation levels. Multiple stepwise regression analyses were performed between AGB and independent variables of spectral and textural properties. The resulted estimation models of AGB within each forest cluster level had R^2 ranging from 0.65 to 0.70 (Pearson coefficient, R = 0.803 - 0.836) compared to 0.61 for a model that combined all forest clusters. In total, forest cluster model (RMSE = 11.38 Mg/ha, relative RMSE = 8.43%) was superior to the combined forest model (RMSE = 13.67 Mg/ha, relative RMSE = 10.12%). Mean AGB of the degraded forest cluster was estimated at 74 Mg/ha (±22 Mg/ha) whereas mean AGB of the late-successional forest cluster was estimated at 236 Mg/ha (±7 Mg/ha). Our study indicates that AGB estimation by specific forest clusters can improve the model and estimation accuracies.

1. INTRODUCTION

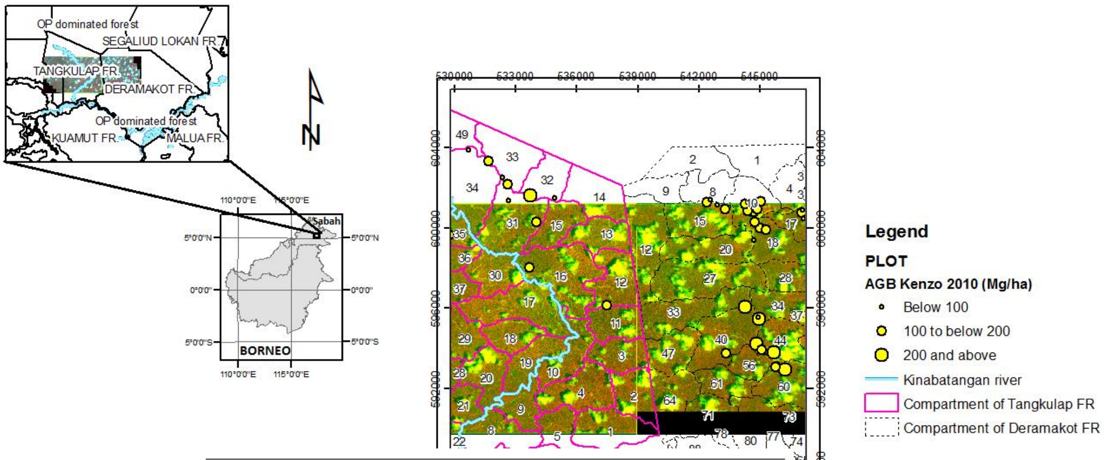
Tropical rainforest consists of a complex layer of tree structures (forest floor, understory, canopy and emergent) (Bongers, 2001). Human disturbances (e.g logging) have significantly altered the composition of forest stand structure. Rainforest can be classified as degraded or non-degraded (or primary forest) forest depending on type of assessments imposed unto it (Kenzo et al., 2009; Eckert, 2012; Langner et al., 2012). Understanding forest degradation level in relation to AGB is increasingly important nowadays (Eckert, 2012; Ioki et al., 2014; Kronseder et al., 2012). It is reasonable to consider differences in canopy texture are related to forest structure and AGB under the canopy.

Degradation influences forest height stand structure which are closely related to regional AGB (Feldpausch et al., 2012). Using various textural and spectral parameters, AGB of a degraded forest was intensely estimated (adjusted R^2 = 0.843) (Eckert, 2012). AGB was always saturated at high biomass level when using pixel-based technique, thus it produced sensible errors (Morel et al., 2011; Thenkabail et al., 2004). With additional textural parameters, significant improvements of forest AGB estimation have been achieved (Eckert, 2012; Wijaya et al., 2010). Langner et al. (2012) estimated AGB in central Sabah based on a compartment basis. Considerable variations within a compartment can be expected since selective logging was in place. In this study, we analysed the degraded forest and estimate the AGB based on a spatial unit smaller than compartment to capture the vegetation community differences within a compartment. We extracted forest canopy structure from an IKONOS-2 image and examined their relations with forest biomass.

2. STUDY AREA

Our study site is located at Tangkulap forest reserve, commercial estate which also known as Forest Management Unit (FMU) 17A and 19A (Figure 1), under the management of Sabah Forestry Department (SFD) Malaysia. The forest reserve is dominated by mixed lowland dipterocarp forest. The forest area is 27,550 ha. Tangkulap is referred to as degraded forest and subjected to different level of degradation due to different timing of compartment-by-compartment logging. The areas was continually logged by conventional logging (CL) system since 1956 (Langner et al., 2012). Somewhere within 1980s until the year of 1995, logging activities in the areas were stopped to allow regeneration of natural resources. A complex balance environment was formed where reduction and restoration of biomass occurred in the ecosystem.

Tangkulap is relatively flat with average elevation of 100m above sea level. Climate is equatorial with two monsoon rain seasons: from May to September and November to March. Mean annual temperature is 28°C while annual rainfall is 3,100mm.



FMU	Name	Class	Area (ha)	Logging since	Ikonos-2 coverage	Remark
17A	Tangkulap	II (Production forest)	27550	1970	60%	Logging ceased in mid-1980s but CL resumed in 1995 until 2002
19A	Deramakot	II (Production forest)	55083	1956	22%	Logging stop in 1989 before RIL resumed in 1995

CL conventional logging, RIL reduced-impact logging

Figure 1: Study site map using UTM (50N) datum; yellow-dotted points (different sizes) represent location and level of AGB by plot

3. FIELD DATA AND IMAGE COVERAGE

Field plots were sampled which were non-uniformly distributed over the areas. For each plot, all trees with dbh ≥ 10cm were recorded. Every plot is round shape with radius either 15 or 20 meters. Plot data are gathered from fieldworks (Oct 2010 until Feb 2013) and Permanent Sample Plot (PSP) of Forest Research Centre (FRC), SFD. AGB allometric equation from Kenzo et al. (2009) was used to calculate the biomass. Since plots were collected from year 2007 until 2012 then a correction of AGB is required according to Clark et al. (2001).

Three scenes of IKONOS-2 satellite image covering a total of 350 square-km, captured on the same day (July 2010), were mosaicked into a single tile. We used 53 ground control points (GCP) to georeference the satellite images. Satisfying error was observed (i.e. RMSE not more than 4 pixels error). The mosaicked image managed to cover about 60% of Tangkulap and 22% of Deramakot area (refer Fig. 1). Basic preliminary processing was implemented unto the image such as pan sharpen and dark object subtraction (DOS).

4. FOREST CLUSTERING

Segmentation was performed using eCognition. The parameter of scales and settings used for the multi-resolution segmentation are listed in Table 1. Notice that selective bands of B, R and NIR were used as input. Sequence of classification was as followed: first, vegetation (forest) was separated from non-vegetation (bare land, water bodies, house-roof, clouds and shadow, and No-data areas) and second is the forest clustering. Feature space optimization function was used to search for the best separation distance and parameter dimension.

Representative plot was assigned to each coincided forest cluster, and if it happens to be more than one plot per cluster, average value was taken. Forest segment classification was based on three types of forest level that are early successional forest (ESF), mid-successional forest (MSF) and late-successional forest (LSF). AGB was used as guidance for classification of forest cluster using such categories: AGB < 100 Mg/ha is ESF, 100 ≥ AGB > 200 Mg/ha is MSF and AGB ≥ 200 Mg/ha is LSF.

Table 1: Multiresolution segmentation and classification of IKONOS-2 image

Band input	Scale; colour; compact; smoothness	Feature Space Optimization settings		Class	Level
		Separation distance	Dimension		
B **R** **NIR**	230; 0.3; 0.8; 0.2	2.691	Standard deviation B Shape index GLCM correlation NIR (135^o) Asymmetry Mean NIR GLCM entropy NIR (0^o)	Forest, bare land, cloud, shadows, water body, house-roof and No data area	Land cover
		0.365	56 various dimensions	ESF, MSF and LSF	Sub forest

5. AGB MODELLING AND VALIDATION

Clusters were separated into each forest category before modelling. Stepwise multiple linear regression analyses were implemented to find out relationship between AGB and other related variables. AGB act as an independent variable. AGB, and its natural log, were used in the analysis. Various spectral and textural properties were the dependent variables.

Since the number of plots in every category was small, we run the estimation model but excluded one plot for validation purposes. This procedure was repeated until all plot have chance to validate. However, for combined forest model, validation was based on group of plots (five plots per group). We selected model performance based on the best value of Pearson coefficient (R) and Coefficient of Determination (R^2).

6. RESULTS

Through the above segmentation procedure and careful selection of the class sample, the IKONOS-2 satellite image was successfully classified into forest, bare land, clouds, shadow, water bodies, house-roof and No-data area. At land cover level, it was distinguished at reasonable separation distance (2.69) using six parameters (Table 1). Mixtures of parameters (spectral, geometrical and textural) were used in the classification. At sub forest level, classification was more challenging with 56 parameters were used to define ESF, MSF and LSF. Separation distance 0.37 indicates low classification accuracies.

Results of modelling can be seen in Table 2. Twenty one clusters were collected for modelling. Range numbers of cluster are between 3 and 12 for each forest level. Two models, forest cluster model and combined forest model, were presented in this study. Both were robustly calculated and moderate performance was selected to represent overall cases. ESF is having strong correlation with single textural parameter (R; 0.80 - 0.84, R^2; 0.65 - 0.70). Meanwhile, MSF and LSF are also have strong correlation (R; 0.80, R^2; 0.64) but with combination of textural and spectral properties. Contrast to forest cluster model, the combined forest model only correlated to spectral parameters. Although strong correlation (R; 0.78, R^2; 0.61) was observed but performance of combined forest model always under the forest cluster model. This reconfirm that forest structure have a specific transitional phase at every level of forest type.

Table 2: Forest AGB modeling and validation

MODEL	Specific cluster level	Model summary						Est. AGB (Mg/ha)		Act. AGB (Mg/ha)			
		N	R^2 (min ~ max)	R (min ~ max)	Dep. var.	Representative model		Ave.	S.D.	Ave.	S.D.	RMSE	CV
Forest cluster	ESF	6	0.699 (0.330 ~ 0.845)	0.836 (0.595 ~ 0.919)	AGB	Constant	861.106	73.62	21.52	73.28	23.22	7.41	10.11%
						GLCM Ang.	-67045.193						
	MSF	12	0.646 (0.603 ~ 0.675)	0.804 (0.777 ~ 0.821)	AGB	Constant	-927.678	142.25	28.32	140.65	31.20	6.32	4.49%
						GLCM Ang.	-7034771.625						
						Mean RDVI	8.837						
	LSF	3	0.645 (0.519 ~ 0.735)	0.803 (0.720 ~ 0.857)	AGB	Constant	561.277	235.96	6.60	235.79	6.61	-	-
						GLCM Con.	-0.175						
						GLCM Ang.	-1864406.303						
	Total	21	-	-	-	-	-	136.54	55.34	135.03	25.21	11.38	8.43%
Combi-ned forest	-	21	0.611 (0.471 ~ 0.656)	0.781 (0.686 ~ 0.810)	AGB	Constant	-126.565	134.99	57.97	135.03	25.21	13.67	10.12%
						Std. dev	2.071						

Note: Dep. Var. is dependent variable, Est. AGB is estimated AGB, Act. AGB is actual AGB, Ave. is average, S.D. is standard deviation, GLCM Ang. is GLCM angular second moment, RMSE is root mean square error and CV is coefficient of variation

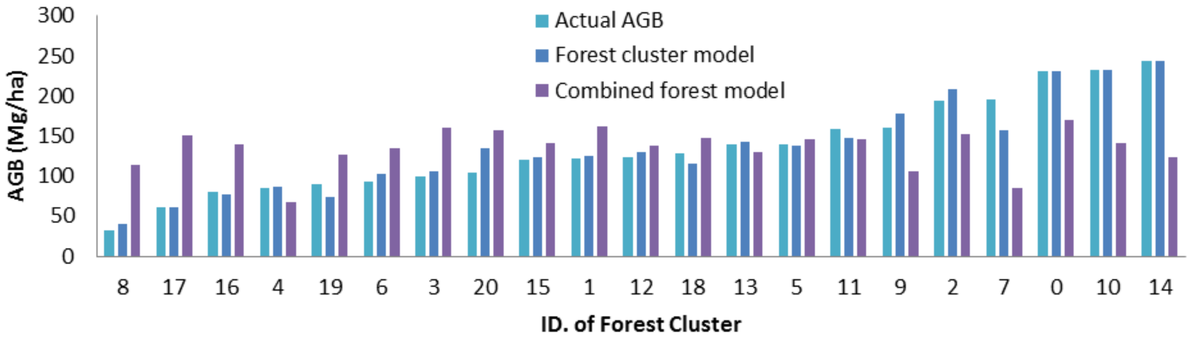


Figure 2: Comparison of estimated and actual AGB

Estimation error was assessed based on RMSE. Accumulated AGB from different forest cluster was total up for comparison with combined forest model. Improvement was obtained through forest cluster analysis (CV = 8.43%) compared to combined forest analysis (CV = 10.12%). Comparison of estimated AGB and actual AGB is showing some agreement for forest cluster model (Figure 2) which solve the AGB saturation problem at high level. There was a clear separation between specific forest model and combined forest model at AGB 200 Mg/ha and above. The combined forest model tends to averagely estimate the AGB. Average of plot forest biomass is 135.03 Mg/ha compare to 136.45 Mg/ha (forest cluster) and 134.99 Mg/ha (combined forest). Figure 3 represents the distribution of AGB, by cluster, inside coverage of IKONOS-2. At Sungai Pinangah (Sg. Pinangah) forest reserve, agroforestry project sites are represented with red colour cluster that indicates low AGB level (below 50 Mg/ha). Judging on size of dbh and height of trees, the replanting project was just initiated.

7. DISCUSSIONS

In this study, we analysed forest canopy surface roughness from IKONOS-2 satellite data and managed to come up with RMSE 20.2 Mg/ha. Lidar exploration on a degraded forest at Central Kalimantan resulted on RMSE variation at 96.7 Mg/ha (Kronseder et al., 2012) and 64.38 Mg/ha (Ioki et al., 2014). Forest stand structure (canopy height) was analysed through distribution of Lidar pulses.

Multicollinearities were not tested in this paper. In stepwise regression modelling, it looks that R^2 increased when more variables were used as predictor but that does not reflect on a good model. Therefore, a strategy of selecting and testing a robust model was implemented in this study.

Area of forest clusters are ranged from 0.4 to 231 ha at Tangkulap where else, level of biomass was 6 kg/ha of minimum and 411 Mg/ha of maximum. This approach assessed AGB in smaller area compared to compartment based assessment (compartment area range from 21 to 992 ha at Tangkulap and 7 to 900 ha at Deramakot) (Langner et al., 2012). In compartment-based assessment, AGB was ranging between 114 and 488 Mg/ha which was calculated using equation provided by Brown (1997). Brown's AGB was nearly twice higher compared to Kenzo et al. (2009).

Assessment of AGB using Landsat ETM+ over vast area in central of Sabah, including Tangkulap, resulted in low R^2 (0.22) and large RMSE (1763.1 Mg/ha) (Morel et al., 2012). Our assessment assessed the forest as separated cluster rather than one entity. Approach in this study was highly dependent on good classification at sub forest level which was not addressed in detail. Forest is classifiable into smaller unit for modelling which may produce more accurate result. Similar approaches using WorldView-2 images over Madagascar's degraded forest has produced RMSE at 31.6 Mg/ha (6.82%) (Eckert, 2012) compared to 11.4 Mg/ha (8.43%) in this study. AGB estimation modelling using SPOT 5 data over the degraded landscape inside Sabah Foundation Concession area in Sabah was underestimated the biomass about 3.2 times lower (Singh et al., 2014).

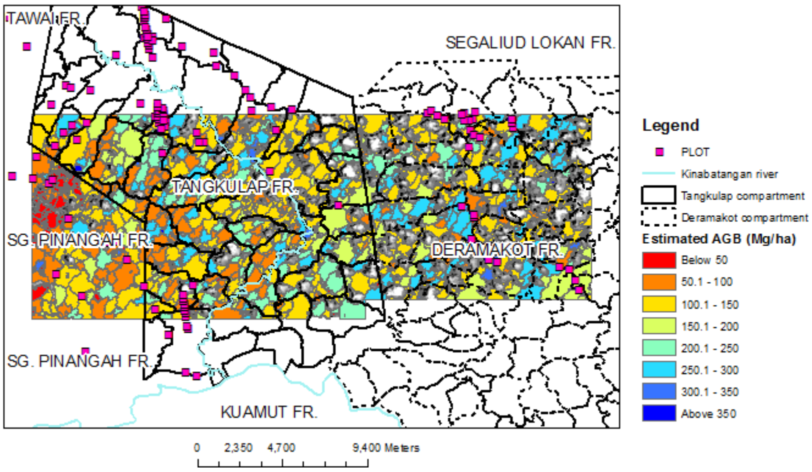


Figure 3: AGB map

Table 3: Summary of AGB distributions by cluster

	Tangkulap		
Cluster	**N**	**AGB**	**%**
Below 50	42	3118.340	0.1%
50.1100	95	226666.529	9.8%
100.1--150	213	848460.276	36.5%
150.1--200	47	244942.627	10.5%
200.1--250	60	497321.297	21.4%
250.1--300	68	447246.540	19.3%
300.1--350	10	36908.450	1.6%
Above 350	4	18342.462	0.8%
Total	539	2323006.521	100.0%

At threshold 200 Mg/ha, percentage of accumulated AGB is 43.1% (Tangkulap).

8. CONCLUSIONS

In this study, potential of high resolution IKONOS-2 data was explored towards AGB assessment of degraded forest. We found out combined forest model was slightly underestimated the AGB compared to forest cluster model which predicts pretty well. RMSE for forest cluster model was also better than the combined forest model. Assessment by forest cluster model solved the AGB saturation problem at high biomass level (at 200 Mg/ha and above). Segmentation of forest into sub forest unit was seemed improves the quality of AGB assessment.

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