BIOMASS OF FIRE-AFFECTED PEAT SWAMP FOREST FROM OBJECT BASED CLASSIFICATION OF QUICKBIRD DATA

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ABSTRACT: Biomass loss and subsequently carbon emission is one of the fire impacts on tropical peat swamp forest. In Klias Forest Reserve, fires occurred in 1998 and 2003. A high-resolution image of QuickBird was acquired for quantifying the above ground biomass of the unburned and burned forests. We used Principal Component Analysis for spectral enhancement of the QuickBird data. The enhanced image was used for image segmentation at several object scales. Each of the scales was interpreted against field data in terms of discrimination of vegetation types as well as tree crowns. Unsupervised classification with K-means clustering was used to classify the objects. We explore the relationship between crown area extracted from the classified tree crowns and diameter at breast height (DBH) measured in the field. Estimation of the biomass based on the relationship of crown area and DBH is possible for upper canopy trees. Although haze and cloud shadow have some inverse effect on the image quality, the object based classification approach provides quantification of the biomass of the fire-affected peat swamp forest.

1.0 INTRODUCTION

Peat swamp forests have a large reservoir of biomass stocks. Peat swamp forest occurred mostly in South-East Asia which estimated about 20 million hectares or two-thirds of the world peat swamp forest (Phillip, 1998). In Sabah, the largest peat swamp forest was found in the Klias Peninsula. Most of the peat swamp forests have been threatened by forest fire and converted into oil palm plantation, agriculture land and human settlement area. Therefore, Malaysia government with the support from United Nations Development Programme (UNDP) initiated the effort to conserve peat swamp forest. In fact, peat land conversion increasing carbon dioxide emissions which may lead to oxidation and peat fires. El-Nino that occurred recently caused deforestation and degradation in huge areas in Borneo (Phua *et al*., 2007; Langner *et al*., 2007). Hence, peat swamp forest is more vulnerable to fire compared to other forest types.

Application of remote sensing for detecting burned areas and biomass estimation is well studied. Satellite remote sensing provides opportunity to monitor carbon changes due to the deforestation and degradation (Asner, 2009). Instead of estimating biomass globally using medium and coarse resolution satellite image, the use of high resolution satellite images has been introduced recently. Biomass estimation using remote sensing is more cost and time effective, as compared to the field inventory method. Hence, multi-spectral high resolution satellite image has been used to examine forest canopy structure using crown detection and delineation method (Pouliot and King, 2005; Pouliot *et al*., 2002). Tree crown detection usually provides information of spatial distribution and tree abundance which is useful for evaluating forest regeneration (Pauliot and King, 2005). Indeed, extracted tree crown information with conjunction of ground measurement data is useful for tree structural modeling (Pouliot *et al*., 2002). For example, DBH and biomass can be estimated through tree crown dimension extracted from satellite data which is useful for growth success evaluation.

While high resolution provides more vegetation information, classification result can be improved. Object based classification has been introduced to overcome the salt-and-pepper effect in pixel based classification (Yu *et al*., 2006; Blaschke, 2010). Object based classification combines homogeneous regions through image segmentation into a group of object. Nevertheless, image segmentation has been used for tree crown detection where a group of pixels represent one crown is combined to become one object. Usually, thresholding and edge detection is used in image segmentation algorithm (Zhang *et al.*, 2005). Thresholding is a way to find difference between object of interest and the background pixels. On the other hand, edge detection is an intensity of an object that moves from high to low value.

Although there is large scale biomass estimation studies using coarse resolution satellite image have been carried out in Borneo, there is still lacking of biomass study using high resolution satellite images. In this paper, we attempt to investigate relationship of crown parameters from Quickbird data with ground measurement data. Biomass of peat swamp forest is estimated based on segmentation of the Quickbird data.

2.0 MATERIALS AND METHODS

2.1 Study Area

Our study is located at Klias Forest Reserve (Figure 1), one of the protection forests in Sabah. Previously, Klias Forest Reserve is a production forest and later was gazetted as forest reserve in 1984. The most dominant species found is *Dryobalonops rappa* (Kapur paya) which covered the upper canopy of peat swamp forest. Selective cutting practiced previously influenced the dominance species especially *Dactylocladus stenostachys* (jongkong) and *Gonystylus bancanus* (ramin) due to the high market demand and easily to transport. Kapur paya have not been cut because it is not a commercial species, uneasy to transport and tend to sink in water. There is an uneven forest structure and floristic components depending on the depth of the peat and distance from the dryland (Sabah Forestry Department, 2005).
The most significant thread to the peat swamp forest is fire. It was affected by fires in 1998 with the total burnt areas estimated about 12,000 ha (Phua *et al*., 2007). Binsulok Forest Reserve is a most affected area. Accessibility is a major factor that influence the fire control. Besides that, building of fire barriers preventing fires from spreading during forest fire. The second forest fires, which occurred during El-Nino in 2003 burned at the most previously burned areas (Phua & Tsuyuki, 2008).

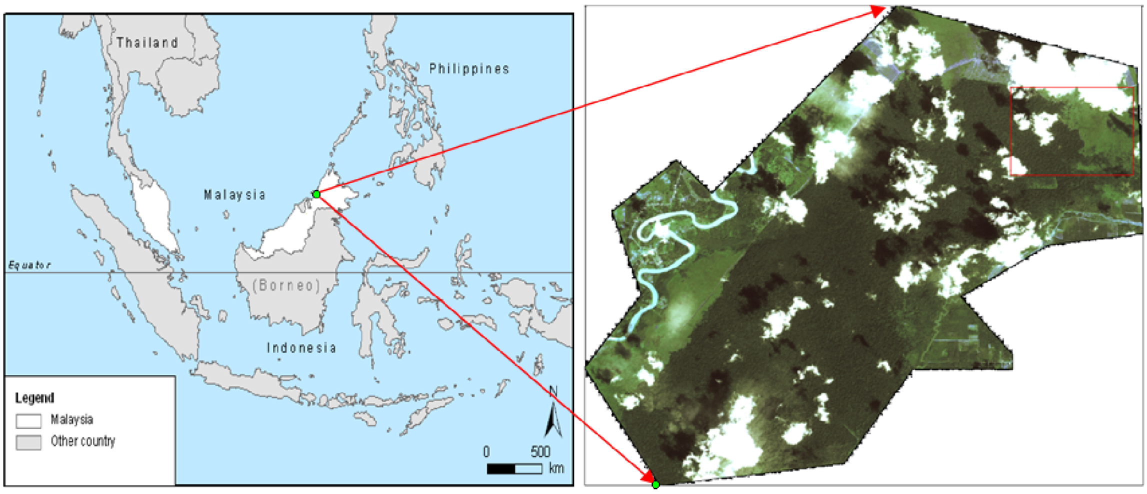


Figure 1. Location of the Klias Forest Reserve and the Quickbird Image (Note: Red box is the burned area)

2.2 Field Data

A total of 8 plots with 20mx20m were carried out on January 2010 for good peat swamp forest field measurements. Diameter at breast height (DBH) and tree height (Ht) have been measured with trees bigger than 10cm DBH. GPS point for each plots were taken in the field. On the other hand, field measurement for burned over peat swamp forest was taken on the year of 2008.

2.3 Quickbird Data

Quickbird image covering Klias Forest Reserve on February 4, 2005 has been acquired. The study site was located at the northest part of the Klias Forest Reserve. Pan sharpening of 2.4 m multispectral Quickbird data has been carried out with panchromatic band 0.6 m. Cloud, shadow and forest gaps have been removed in order to avoid over estimation of crown area. A 3x3 majority filtering has been applied to the pan-sharpened image. After that, Principal Component Analysis (PCA) was used to enhance the image before segmentation. PC1, PC2 and PC3, constitute % data variance were selected for image segmentation.

The Quickbird data was segmented using multiple scale based on three parameters, namely scale, color and form. Firstly, edge detection was performs on the Quickbird image. Segmentation was performed using the detected edges as boundaries of the segments. The segmentation's results of different scale were examined until the best representation of the land cover is matched. Unsupervised K-means clustering with 15 classes was performs where each segments were assigned into a closest cluster means. The 15 classes were refined into six major classes using ArcGIS. Spectral values for the same crown in the Quickbird image exhibited variations. Therefore, a forest tree crown was divided into three classes namely bright, medium and dark parts of a crown. Other land covers classes included inside object based classification were young regenerating, grassy vegetation, bare and shadow.

2.4 Segmentation Accuracy Assessment

Segmentation accuracy was assessed as goodness of the segments (Clinton *et al.*,2010). The reference layer for the tree crowns were digitized manually for each plots. The number of crowns on the reference layer were compared with the number of crowns on the segmented layers. The tree crown arrangement for both reference layer and segmented layer was tallied. Therefore, we calculted the subset area for each crowns to determine the intersection area between reference object and segment object. Let $X=\{x_i: i=1......n\}$ and $Y=\{y_j: j=1......n\}$
where, X is a reference object and Y is a segment from the segmentation. Meanwhile, the intersection of the segment with the reference objects mean it is a matching crowns area. According to Clinton *et al.* (2010), properties of the segments define as below:

Oversegmentation= $\mathbf{1}-\frac{area(xi\cap yj)}{area(xi)}$, Undersegmentation= $\mathbf{1}-\frac{area(xi\cap yj)}{area(yj)}$

The range is [0,1], where oversegmentation=0 or undersegmentaion=0 means there is a perfect segments. The closeness index, D is used to evaluate the quality of the segmentation, where

$$D=\sqrt{OverSegmentation^2+UnderSegmentation^2}$$

2.5 Data Analysis

The segmentation's result was compared with the field data to indentify the individual trees in the field. The trees number for each plots on the Quickbird image were counted. The numbers of trees from field survey were compared with the number of tress derived from the Quickbird image. However, lower canopy trees cannot be observed from the satellite. Hence, we assumed that individual trees obtained from the Quickbird data and field survey corresponding according to the largest tree to smaller tree. We derived crown parameters such as perimeter and area from the segmented tree crowns. We assumed that crown area derived from the Quickbird corresponding to the field measured DBH, crown width and tree height. Estimated crown diameter from the Quickbird data was calculated from crown perimeter. Therefore, we investigate the relationship between crown area and crown diameter from the Quickbird data and ground measured DBH. Linear regression of crown area and DBH from field survey was performed to investigate their relationship, as follows:

$$\boldsymbol{DBH_{QB}} = (\mathbf{a} \times \boldsymbol{CA_{QB}}) + \mathbf{b}$$

where a and b is the constant of the regression, CA_{QB} is the crown area estimated from Quickbird data, and DBH_{QB} is the estimated DBH from the Quickbird data.

Biomass for good peat swmap forest was calculated based on the Siregar *et al*., (2005) equation, where

Biomass = 0.1035 x $(\mathbf{DBH^2})^{\mathbf{1.2789}}$

Estimated biomass from Quickbird data and actual biomass from the field measurement were compared to examine the accuracy of biomass estimates.

3.0 RESULT

The overall mean for DBH and tree height for 8 plots is 27.2cm and 23.2m respectively. However, for crown parameter, the overall mean crown area and crown diameter is 38.4m^2 and 6.2m respectively.

3.1 Land Cover Classification Using Quickbird Data

The result of the object-based classification is shown in Figure 2. The overall land cover classification accuracy is 80.8%. Meanwhile, Kappa accuracy and unbiased accuracy measurement of land cover classification is 75%. With a total area of 374.2 ha, 67.5% (252.4 ha) is forest tree class. The grassy vegetation covers 14.5% (54.1 ha) of the study area. The regenerating forest covers slightly lower than grassy vegetation, which occupied 10.1% (37.6 ha). Lastly, the bareland occupied only 2.8% which only 10.6 ha of the study area.

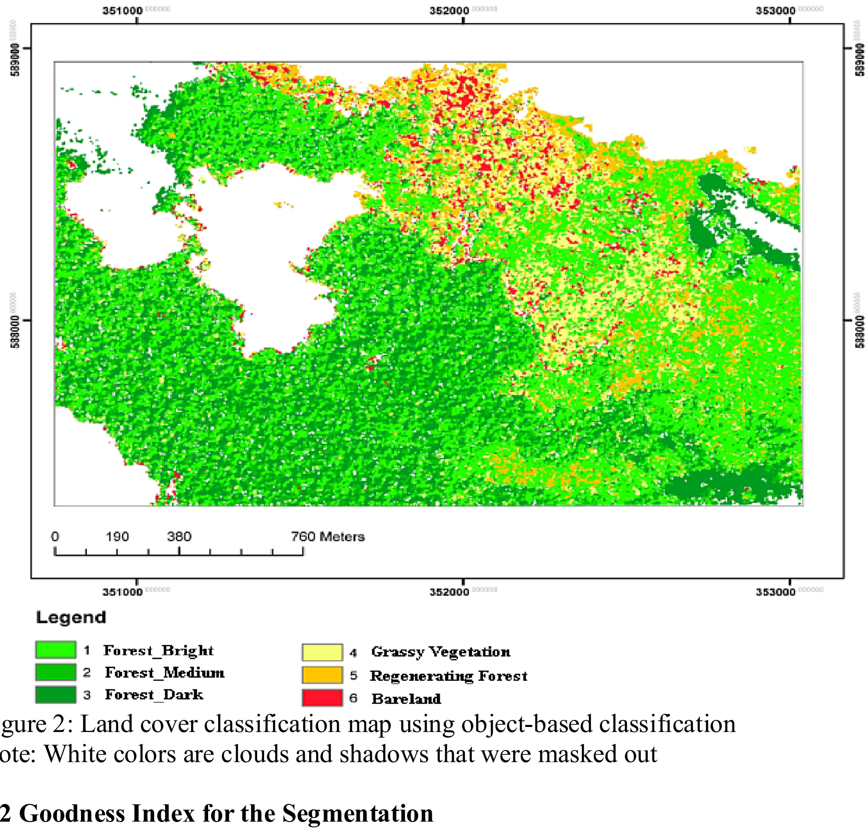


Figure 2: Land cover classification map using object-based classification
Note: White colors are clouds and shadows that were masked out

3.2 Goodness Index for the Segmentation

The number of trees from the field measurement and automated segmentation from the Quickbird image showed that there is a similarity for plot 1, plot 4 and plot 7. Plot number 8 showed a highest different between numbers of trees from the field measurement and number of trees detected from the Quickbird image. This study indicates that automated segmentation methods applied is reliable for tree crown detection. The overall closeness index of the segments to the ideal tree crowns was 56% in this study.

No of trees	Field	QuickBird(Segmented)	QuickBird(Digitized)
Plot 1	12	12	12
Plot 2	8	5	7
Plot 3	18	12	15
Plot 4	9	9	12
Plot 5	12	10	15
Plot 6	9	8	13
Plot 7	7	7	12
Plot 8	19	9	15
Total	**94**	**72**	**101**

Table 1: The number of trees from field work and the QuickBird image

3.3 Biomass Estimation

The correlation analysis showed that field measured DBH (DBH_f) and crown area from automated segmentation has a highest correlation with R = 0.571, $p < 0.05$. Therefore, crown area from automated segmentation was used for building relationship between crown area from Quickbird data and ground measure DBH. Linear regression with enter method was chosen in this study. The regression model resulted from the regression has a R^2 of 0.316 ($p < 0.05$).

$$\boldsymbol{DBH_{QB}} = (0.347 \times \boldsymbol{CA_{QB}}) + 11.783$$

From the equation above, DBH_{QB} of unburned peat swamp forest was estimated with average 26.3 cm for 8 plots. Overall biomass were estimated using estimated DBH_{QB} based on Siregar *et al.*, (2005) equation. The biomass estimated in this study was 50.67 tonnes. Meanwhile, field measured biomass biomass was 59.6 tonnes. The result showed that this study was able to measured biomass with the accuracy of 85% , with 15% biomasss was underestimated in the plot level.

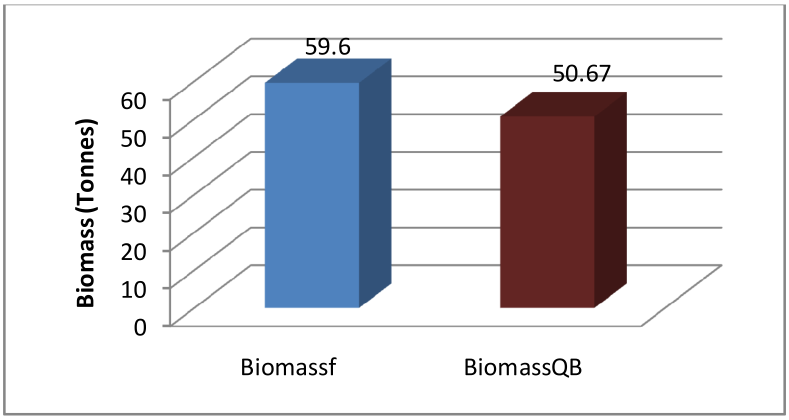
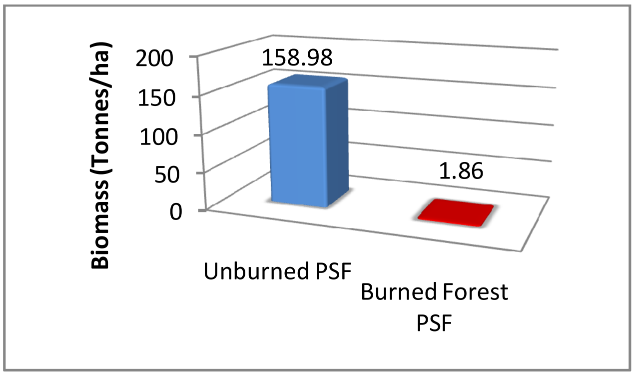


Figure 3: Biomass estimated from Quickbird dataversus field measurement at plot level

Nevertheless, biomass for unburned peat swamp forest is higher than biomass of burned peat swamp forest with 158.98 tonnes per hectare and 1.86 tonnes per ha respectively. Overall biomass of 374.2 ha in this study is 40,124.69 tonnes occupied by unburned peat swamp forest and 100.45 tonnes for burned peat swamp forest.



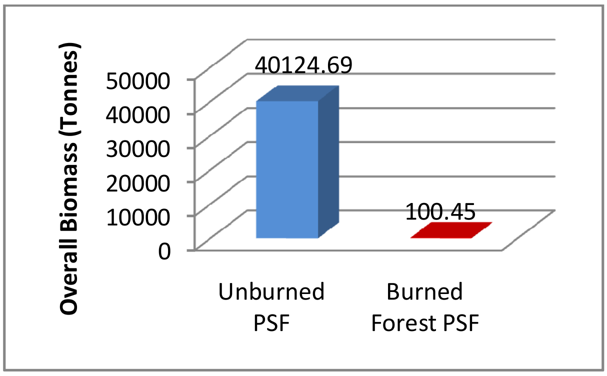


Figure 4a: Biomass per hectare of unburned and burned peat swamp forests
Figure 4b: Overall biomass of unburned and burned peat swamp forests

4.0 DISCUSSION

Peat swamp forest in Klias Peninsula is formed on a dome shaped peat with peat the highest of peat depth approximate 14m. Due to the dome shaped peat, rainfall is the only source of water. and the soil fertility is low. Therefore, occurrence of small trees is high in peat swamp forest (Phillip, 1998) and less in Klias Peninsula (UNDP, 2006).

They were various factors influencing the accuracy of crown size extracted in this study. The most important factor was the timeline between data acquired date and field data collection. In this study, the Quickbird data was acquired in the year 2005, meanwhile the field data collection was conducted in the year 2010. Therefore, there was 5 years different of time line. The tree crown size is slightly different between Quickbird data and ground measured data due to the growth between this timeline (Song *et al.*, 2010). In fact, image acquisition is depending on the weather atmospheric. The best image for segmentation is cloud and haze free. Besides that, we were assumed that trees crown size is circular shape rather than eclipse. In fact, tree crowns in natural forest are more likely to be irregular circular shape. Therefore, there were be differences between actual tree crown area and calculated tree crown area.

Although crown area and crown diameter extracted from automated segmentation were well correlated with the DBH from field measurement, there were several limitations applying automated segmentation on natural forest. Clumps of small trees and continuous tree crowns were likely to be detected as one crown and covered by big trees which form the emergent canopy. Low variation of spectral values between crown boundary and within crown as well as overlapping continuous tree crowns are likely to increase the detection error (Pouliot *et al.*, 2002). Therefore, smaller trees or suppressed trees were difficult to be detected from the segmentation of Quickbird image. Besides, continuous tree crowns were difficult to separate. Plot No 8 showed a highest error of tree crown detected because 40% of the trees were small trees with DBH less than 15cm. The presence of short ground vegetation contributed the tree crown detection error as well (Pouliot *et al.*, 2002). The spectral reflectance between short ground vegetation and trees is quite similar, hence it is most likely to be detected as tree apex instead of adjacent trees.

Figure 5 showed that burned peat swamp forest only occupied 0.25% of the overall biomass in this study area. Overall unburned peat swamp forest still contributing 99.75% of total biomass. Lower biomass in burned peat swamp forest was mainly due to the repeatly burnt and left over grassland. Although it has been repeatly burned, unburned peat swamp forest still contributing highest biomass values. Therefore, fire management should be taken in order to prevent fire from spreading into the unburned peat swamp forest areas.

5.0 CONCLUSION

Deforestation of peat swamp forest in Borneo has become an important issue for biomass study. Therefore, uses of high resolution satellite image with accurate and detailed vegetation information such as Quickbird data had been introduced. However, uses of high resolution satellite data only practice in locally due to the cost. This study investigated the potential of using DBH from field measurement and crown area from Quickbird data to estimate biomass for upper canopy. The result showed 1/3 of underestimates of biomass between field measured biomass and estimated biomass. Underestimation was due to the limitation to detect trees for lower canopy on the Quickbird data.

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