Analysis of Canopy Height Model (CHM) Extraction using Quick Terrain Modeller (QTM) for Tropical Forest Area

Nurul Ain Mohd Zaki1*, Muhammad Farhan Rajuli1, Zulkiflee Abd Latif6,2, Mohd Nazip Suratman3, Hamdan Omar4, Sharifah Norashikin1, Mohd Zainee Zainal1 and Noorfatekah Talib1.

1Environment and Climate Change Research Group, Centre for Surveying Science and Geomatics Studies, Faculty of Architecture, Planning and Surveying, Universiti Teknologi MARA, 02600, Arau, Perlis, Malaysia

2Applied Remote Sensing & Geospatial Research Group, Centre for Surveying Science and Geomatics Studies, Faculty of Architecture, Planning and Surveying, Universiti Teknologi MARA, 40000, Shah Alam, Selangor, Malaysia

3Centre for Biodiversity and Sustainable Development, Faculty of Applied Science, Universiti Teknologi MARA, 40000, Shah Alam, Malaysia

4Geoinformation Programme, Division of Forestry & Environment, Forest Research Institute Malaysia (FRIM), 52109 Kepong, Selangor, Malaysia

Email: nurulain86@uitm.edu.my

Abstract. Forest biomass or above-ground carbon stock is the mass of carbon that stored in trees which requires a continuous monitoring in order to predict the amount of potential carbon accumulation of the forest. Therefore, the forest has an important role at absorbing carbon Dioxide (CO$_2$) from the atmosphere. This research aims to measure the capability of Quick Terrain Modeller software at estimating above-ground carbon stock by single tree segmentation combining ground inventory, Light Detection and Ranging (LiDAR), and by using allometric equations. In particular, to achieve the aim, there are three (3) objectives were outlined. Canopy Height Models (CHM) was generated via Quick Terrain Modeller (QTM) and ArcGIS. Non-linear Regression analyses were performed for both surface models to ensure the models were fit to estimate carbon stock. Secondly, tree contours were delineated using watershed transformation. Local maxima were determined at the raster as a pour point for watershed and also represent the highest peak of the tree crown. In addition, flow direction, drop output, and flow accumulation of the raster were also determined to generate contour from the watershed transformation. Manual tree crown projection was performed by watershed tree contour to generate Crown Projection Area (CPA). Then, from the digitized CPA, carbon stock and above-ground biomass was calculated using equations from [1] and [2]. Thirdly, tree species on the selected area were extracted and finally a map of tree carbon stock by species was produced. From the generated map, total carbon stock according to species and total carbon stock in single tree according to species information were extracted. As a result, *Hopea sulcata*; the endangered tree species appeared to be the highest appearance in the map followed by *Dipterocarpus verrucosus*, *Shorea macroptera*, *Endospermum diadenum*, and the other less appeal species. Also from the map, *Hopea sulcata* has the highest carbon stock which is 23% compared to the other species. However, for a single tree, *Dipterocarpus verrucosus* held the highest carbon stock which is 1565.401 kg/tree.
1. Introduction

The tropical biomass has become one of the biggest factors to be addressed when it comes to climate change and global warming. One of the reasons regarding tropical biomass is its carbon circle [3]. This has become more crucial to address the tropical forest as for the forests’ nature at having a vast species for each different layer. When it varies in species, the density of carbon in the forest differs from each other.

Malaysia has intensified researches on carbon stocks and new data have been generated. Many studies have been carried out to determine the allometric equation for biomass estimation such as [4] and [5]. However, extrapolating the result to an entire country is difficult and only few had really developed new function based on actual dataset. A comparison of approaches for estimating biomass in every area revealed not only a wide range of estimations (lowest and highest estimation), but also difficulty in finding an agreement on which estimation is the best [6].

In conjunction to that, there are two methods that can be applied at efficiently estimating forest biomass and carbon stock. First is via field sampling. The sampling techniques is accurate but may only cover small area and mainly focused on limited components such as tree density, tree species and family, and also basal area [7]. Ground inventories link tree metrics to their biomass using allometric relationships and then distribute the estimated value to the whole forest stands and to entire forest ecosystems. The irregular forest density and complex vertical forest structure prevents the surveyor to easily collect the tree crown edge and also tree height from the ground. Since only selected samples were taken on the research area, it may not be efficient to represent the whole forest as it was not suited to indicate the whole forest area [7]. In addition, this also leads to the uncertainty in estimating forest biomass and carbon stock for the whole forest structure [8].

Another method is via airborne LiDAR. The LiDAR system is a pulsed laser unit which can operate in either a profiling or scanning mode from an aircraft platform. Only profiling data were examined in this study, the nitrogen laser can emit up to 400 pulses of lights and photomultiplier tubes measure the returns from each pulse [9]. The airborne LiDAR creates a close link between biophysical characteristics and vegetation height of the trees [10]. In addition, the tree height obtained from airborne LiDAR also may become a good predictor for biomass and carbon stock estimation in large area of study [11]. According to [2], regression equations are used in most of the studies that occurred in tropical forest to build the relationship between AGB and airborne LiDAR such as [12]; [9] that used linear model. Also non-linear transformation model was used by [13] while [14] used logarithmic model.

As for that, this article focused on the watershed transformation approach at providing an accurate contour layer for manual CPA delineation and highlights the credibility of the LiDAR processing software; Quick Terrain Modeler (QTM) at generating a good Canopy Height Model (CHM) for carbon stock and forest biomass estimation. In practice, CHMs are available in raster formats and can be considered as 2D images where individual tree crowns are often visually noticeable. To delineate tree crowns or detect individual trees from the CHM, a variety of algorithms or procedures have been devised or explored across various forest conditions, which include but are not limited to image segmentation, local maxima filtering, and template matching [15]; [16].

Furthermore, this paper integrates both field data and airborne LiDAR data for carbon stock and forest biomass estimation. This paper also emphasizes the allometric equation by [2] for the predicted carbon and [3] for the observed carbon. Both results were analyzed the relationship of both allometric equations by using non-linear regression method. The non-linear regression analysis also was used to determine the relationship between CHM generated from QTM and ArcGIS, and height from CHM and height from field observation. This leads to the aim of the study at measuring the capability of QTM software at estimating above-ground carbon stock by single tree detection at Ayer Hitam Forest Reserve (AHFR).
Hence, the objectives of this research are; (i) to analyse CHM using Quick Terrain Modeler and ArcGIS; (ii) to delineate tree contour and individual tree detection by watershed transformation using ArcGIS, and (iii) to calculate above-ground carbon stock and produce analytical map of carbon stock by tree species.

2. Material and Methods

2.1. Study Area
The study area is located in Selangor, a state that neighbours Wilayah Persekutuan Kuala Lumpur, Perak, and Negeri Sembilan. The forest reserve is located in the middle of a relentless urban development of Puchong at 3º00’15” N and 101º38’17” E. The gazetted forest reserve was some 4000 hectares back in 1906 and now to just 1248 hectares. Managed by Universiti Putra Malaysia, the forest reserve is only about 20 kilometres away from the university [2]. Interestingly, the AHRF is a home for almost 127 species that also includes at-risk species [17].

Figure 1. The Worldview-3 image in RGB of AHFR.

2.2. Airborne LiDAR
The first data is the airborne laser scanning data point clouds. Laser scanning data is mainly used to estimate the CHM and the classification of forest layer. The data also will be used to estimate above-ground biomass based on tree height and diameter breast height (DBH). Table 1 shows the airborne parameters used for this study.

| System                | LiteMapper-Q560 |
|-----------------------|-----------------|
| Scan Angle            | 45º             |
| Pulse Frequency       | 150kHz          |
| Overlap               | Side overlap 40%, frontal overlap 60% |
| Swath Width           | 1155m           |
| Ground Speed          | 90knot          |
| Flying height         | 1000m           |
| Laser scan angle      | Min 426º, Max 60º |

2.3. Ground Inventory Data
Secondly, the data used for this study is ground inventory. In the study area of 2 hectares, there are 32 subplots were establish at the site. Within the study area as well, the trees structure information were taken. The ground inventory data collected consist of coordinates of the trees where the data were taken.
in X, Y, and Z by real time kinematic method via GPS, tree species by leaf backbone identification, diameter breast height that was measured using tape at 1.3m above tree stem, and also crown diameter that is used to project crown in tree delineation process

2.4. Generation of CHM using QTM
From QTM, the laser point cloud format (.las) was used to generate CHM and displayed as Ungridded Point Cloud (.qtc) format in the software. In order to generate a good CHM, the laser point clouds for DEM and DSM has to be rasterised first and converted to Gridded point Cloud (.qtt) with grid sampling of 0.2311. Adaptive Triangulation method was selected for hole filling with Maximum Z as the algorithm. Moreover, it also gives antialiasing towards the raster where the model will appear less coarse. Spikes were also removed in the conversion tool of from the software. The generation of CHM was done using Subtract Model editing tool. In order to make the CHM fit, Above-ground Level (AGL) Analyst tool was used to draw the lowest elevation close to 0m.

2.5. Generation of CHM using QTM
In ArcGIS 10.2, the laser point cloud format has to be placed in LAS dataset file (.lasd). As for that, the DSM and DEM from (.las) file have to be converted to LAS dataset first. In LAS dataset, classification was made using statistic function where it calculates RGB features in the laser points. Also, the property of LAS dataset allows us to set the XY coordinates of the study area. UTM 47N zone was selected as the coordinate system in use for this research. The LAS dataset was rasterized while having the hole filled automatically using natural neighbour feature. Finally, the Minus tool in ArcGIS will create the CHM by subtracting DEM and DSM.

2.6. Projection of Tree Contour Using Watershed Algorithm
The reason to use these algorithms is because it already gives connectivity and homogeneity within the subject and both processing use markers to detect treetop. However, in this study, the watershed algorithm was only used to generate tree contours. The ground inventory tree ID was used as the marker for tree top detection. In the algorithm, there will be markers with illustrated holes at the prescribed points [18]. In this segmentation process, the amount of delineated tree crown is said to be equal to the number of markers used. The selections of markers as treetop were preferred in order to avoid false trees.

2.7. Generation of Feature Extraction
The features were extracted in order to be used as the variables in non-linear regression analysis as an explanatory variable. The DBH was extracted from field measurement while tree height was extracted from CHM. CPA for this research was extracted from manual tree crown delineation. The manual digitizing method was selected because it allows independent selection toward best and visible tree crown contour from the Watershed raster. The amount of extracted tree crown was 126 units of tree varying in 8 different species. The biggest tree crown was *Shorea Dasyphylla* with 318m\(^2\) tree crown area while the smallest tree crown was *Santiria Apiculata* with 12m\(^2\) tree crown area.

2.8. Generation Above-ground Biomass and Carbon Stock Calculation
The calculation of the carbon stock and above-ground biomass (AGB) was done by using allometric model. In order to calculate carbon stock, AGB has to be measured first. The carbon stock for each trees were used as a dependent variable in the regression analysis. As for that, for predicted value of carbon stock from LiDAR, the formulas involved were from [2] while the observed value of carbon stock from ground inventory used formulas from [1].

2.9. Allometric Equation for Aboveground Biomass Estimation
In this allometric equation (Equation 1), the predictors used were observed height from LiDAR (hL) and CPA (CPA). The (hL) was extracted from the CHM and comes in metres while the CPA which measured
in $m^2$ was extracted from the output from the segmentation [2]. In this case, the manually projected CPA is important to ensure that the equation works best on the individual tree as it also involves tree species.

$$\text{AGBest} = -5.963 + 3.130 \ln hL + 0.524 \ln \text{CPA}$$

(1)

Furthermore, with the developed AGBest from equation 1, carbon stocks from the individual tree can be calculated. In the next equation (Equation 3), carbon stock represents “Sc” in the equation and only the AGBest required developing carbon stock estimation.

$$\text{Sc} = \exp(\text{AGBest})$$

(2)

In this equation (Equation 3), the researcher has developed a list of wood density according to each species. As for that, wood density would be used in the $\text{AGB}_{\text{est}}$ equation that will give a more accurate estimation for the trees. In Chaves et al. (2014) equations (Equation 4), the predictors involved are wood density ($\rho$), DBH (D), and height observed from ground (H).

$$\text{AGB}_{\text{est}} = 0.067(\rho D^2H)^{0.976}$$

(3)

Next, from the result obtained from Equation 4, we can calculate the carbon stock. According to IPCC (2006) the amount of carbon stock in a tree is half the AGB of the tree. As for that, IPCC (2006) has set the constant to convert AGB to the carbon stock using the conversion of Equation 4.

$$S_c = \text{AGBest} \times 0.47$$

(4)

3. Analysis and Discussion

3.1. Description Analysis

In this study, limitation was set by only focused on the dominant and co-dominant species in which is height is equal and more than 25m [12]. The reason is because the dominant and co-dominant trees were crucial to estimate in order to imply the Selective Measurement System (SMS) as a normal practice of the logging activities in Malaysia. As for that, there are in total of 126 trees detected for dominant and co-dominant trees within the area of interest. Among the trees, there are in total of 59 tree species with their significant carbon stock. The tree species were classified into eight classes of the dominant species from which the most appealing species are classified. For the other species that appear with just three or less tree, it was classified into “other” class as shown in Table 2.

| Tree Species             | Number of trees |
|-------------------------|-----------------|
| Dipterocarpus verrucosus| 10              |
| Endospermum diadenum    | 6               |
| Hopea sulcata           | 12              |
| Koompassia malaccensis  | 3               |
| Payena maingayi         | 5               |
| Shorea dasyphylla       | 3               |
| Shorea macroptera       | 9               |
| Others                  | 78              |
3.2. CHM Generation using QTM

The result for CHM was 44.893m as the highest point and -0.374m stands the lowest point. As seen on Figure 3 and Figure 4, the 2D viewing shows that the red spot is the highest at the ground while the blue colour is the lowest. The same goes to Figure 4 below with its height classification in 3D.

![Figure 2](image1.png)

**Figure 2.** Canopy Height Model (CHM) using Quick Terrain Modeller (QTM).

![Figure 3](image2.png)

**Figure 3.** Canopy Height Model (CHM) 3-Dimension using Quick Terrain Modeller (QTM).

Furthermore, the model will lose some of its point as the interpolation happens. In the software, as Adaptive Triangulation was used, it affected some of data loss. Table 3 shows how the data has taken changes between models. CHM has the lowest points (originally laser point data) among three of
them. This happens when the model subtraction happens. Originally the first value is DSM. After undergoing the subtract model process, the laser point decreases.

| Points   | DSM  | DEM  | CHM  |
|----------|------|------|------|
|          | 448,998 | 15,390 | 447,764 |
| Density  | 18.724  | 0.642  | 18.724  |
| Min      | -27.870 | -27.961 | -0.374  |
| Max      | 41.320  | 6.180  | 44.893  |
| Mean     | 9.361   | -12.374 | 21.737  |
| Standard Deviation | 12.178 | 9.406 | 7.807  |

3.3. **CHM Generation using QTM**

In ArcGIS, the Laser Point Data (.las) has to be converted into LAS Dataset in order to perform further processing in the software. In this GIS-based software, it is still considerable software to perform surface model generation. On the other hand, CHM creation does not have the precaution regarding the spike that occurs in the model data. As a result, the highest point at the CHM was 44m and the lowest was -1m as shown in Figure 4.

![Figure 4. Canopy Height Model produced using QTM](image)

3.4. **CHM Generation using QTM**

As how the non-linear regression has pictured in Figure 5, the starting height for tree prediction was 20m while the highest point would be 34m. The result shows that the LiDAR data has a slight difference with the height measured at field. However, it can still considered that the LiDAR data was accepted as it has a positive moderate correlation with height from the field at $R^2=0.62$ that is considerable to be close to 1. The second order polynomial shows the highest $R^2$ compared to other type of regression which is linear, logarithmic, power and exponential. However, from the processed data, the LiDAR data is acceptable to be used as inventories in forestry.
Figure 5. Scatter plot of predicted height from QTM against observed height at field in meter.

3.5. Watershed Transformation Algorithm
By preparing local maxima, flow direction, drop out raster, and flow accumulation raster, the information needed to perform watershed transformation has completed. A watershed is the upslope area that contributes flow that is generally water to a common outlet. In this case, the pour point on the surface will be the point of the water to flow for an area. In order to enhance the watershed polygon, SetNull function was used. The height that was below 25m was removed and set as no data using equation 5. The result of removing height below 25m was shown in Figure 6.

\[ \kappa = \text{SetNull}("elev" < 0, "elev") \]  

(5)
3.6. Tree Crown Delineation

In this research, tree crowns from the rasterized LiDAR CHM model were extracted manually based on contour of local maxima generated by watershed transformation algorithm in ArcGIS. Manual single delineation was done in ArcGIS. This method gives the opportunity for the processor to choose best tree that is seen, fit, and does not overlap with other trees. As shown in Figure 10, the tree crowns were carefully digitized and delineated one by one for each identified tree IDs. All of the delineated tree crowns were dominants and co-dominants tree in the area of interest.

3.7. Aboveground Carbon Stock RMSE Verification

Root Mean Square Error (RMSE) was used to validate the carbon stock and to see errors between both carbon Stock equations; [2] as predicted value and [1] as observed value. Using the RMSE formula (Equation 6), the result was finally tabulated in Table 4.

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{n} (P_i - O_i)^2}{n}}
\]  
(6)
Table 4. RMSE verification.

|       | Total   | SSY     | RMSE   |
|-------|---------|---------|--------|
| n     | 126     | 831.84  | 0.653378 |
| Chave et al (2014) | 832.6705262 |        |        |
| Mohd zaki et al (2018) | 842.9003133 |        |        |
| Error | 10.22979 |         |        |
| $O_2$ | 5580.773758 |        |        |
| $(P_1-O_1)^2$ | 82.32558715 |        |        |

Figure 8. Species composition.

As illustrated in Figure 8, Hopea sulcata has the highest carbon stock which was 23% while the least carbon stock in the study area was Pellacalyx saccardianus at only 2% followed by Payena Maingayi at only 8%. However, for a single tree, Dipterocarpus verrucosus held the highest carbon stock which is 1565.401 kg tree$^{-1}$. However, Hopea sulcata that has the highest carbon stock in the study area only stores 390.731 kg tree$^{-1}$ in a single tree. This means that Dipterocarpus verrucosus species has lesser trees in the study area compared to Hopea sulcata.

4. Conclusion

In conclusion, the selection of QTM LiDAR processing software is capable of generating a good CHM for further analysis as it shows a good significance with the ground inventory. Moreover, the study proved that the Watershed contour is gives a better outcome for manual tree crown projection. This project also used two formulas to estimate carbon stock in which the formula from [2] was used for predicted carbon while [1] was used for observed carbon stock. As for that, this research also proved that the estimated carbon stock can be used to map out carbon stock by species and trees at AHFR.

Moreover, the $R^2$ and RMSE resulting from this study is said to be accurate and acceptable to the analysis as the value ranging from 0.5 to 0.6. This means that the results is significant and have a strong relationship towards each other. The CHM smoothing also plays an important role as it influences the quality of tree delineation. As for that, the 4x4 search window for tree crown delineation minimizes the error from the manual digitization.

Also in this research, the aim and all the objectives stated were achieved successfully and the research questions were all answered. The result from CHM generated from QTM has proved to be good and accurate for carbon stock estimation. Consequently, the Watershed algorithm also provides contour that gives accurate visualisation of the tree crown. Lastly, the above-ground carbon stock estimation also gives a positive significant relationship between predicted and observed value of carbon. However, the carbon stock calculation in lowland Dipterocarp forest at AHFR by using parameters of DBH, CPA, CHM are recommended to be used for this kind of research. This is proven because the more parameter used for analysis, the more accurate the result would be. As for that, the final result for carbon stock of the studied area is 124221.5275kg tree$^{-1}$. 

References

[1] J. Chave, M. Réjou-Méchain, A. Búrquez, E. Chidumayo, M. S. Colgan, W. B. Delitti, A. Duque, T. Eid, P. M. Fearnside, R. C. Goodman, M. Henry, A. Martínez-Yrizar, W. A. Mugasha, H. C. Muller-Landau, M. Mencuccini, B. W. Nelson, A. Ngomanda, E. M. Nogueira, E. Ortiz-Malavassi, R. Pélassier, P. Ploton, C. M. Ryan, J. G. Saldarriaga, and G. Vieilledent, “Improved allometric models to estimate the aboveground biomass of tropical trees,” Global Change Biology, vol. 20, no. 10, pp. 3177–3190, 2014.

[2] N. A. M. Zaki, Z. A. Latif, and M. N. Suratman, “Modelling above-ground live trees biomass and carbon stock estimation of tropical lowland Dipterocarp forest: integration of field-based and remotely sensed estimates,” International Journal of Remote Sensing, vol. 39, no. 8, pp. 2312–2340, Sep, 2018.

[3] H. Omar, M. H. Ismail, K. A. Hamzah, H. Z. M. Safri, and N. Kamarudin, “Estimating Biomass in Logged Tropical Forest Using L-Band SAR (PALSAR) Data and GIS,” Sains Malaysiana, vol. 44, no. 8, pp. 1085–1093, Jan. 2015.

[4] R. Kato, Y. Tadaki & H. Ogawa, “Plant biomass and growth increment studies in Pasoh forest,” Malayan Nature Journal, 1978.

[5] T. Kenzo, R. Furutani, D. Hattori, J. J. Kendawang, S. Tanaka, K. Sakurai, and I. Ninomiya, “Allometric equations for accurate estimation of above-ground biomass in logged-over tropical rainforests in Sarawak, Malaysia,” Journal of Forest Research, vol. 14, no. 6, pp. 365–372, 2009.

[6] R. A. Houghton, “Aboveground Forest Biomass and the Global Carbon Balance,” Global Change Biology, vol. 11, no. 6, pp. 945–958, 2005.

[7] A. Ferraz, S. Saatchi, C. Mallet, and V. Meyer, “Lidar detection of individual tree size in tropical forests,” Remote Sensing of Environment, vol. 183, pp. 318–333, 2016.

[8] A. Fayolle, J.-L. Doucet, J.-F. Gillet, N. Bourland, and P. Lejeune, “Tree allometry in Central Africa: Testing the validity of pantropical multi-species allometric equations for estimating biomass and carbon stocks,” Forest Ecology and Management, vol. 305, pp. 29–37, 2013.

[9] H. Latifi, F. Fassnacht, and B. Koch, “Forest structure modeling with combined airborne hyperspectral and LiDAR data,” Remote Sensing of Environment, vol. 121, pp. 10–25, 2012.

[10] S. E. Reutebuch, H. E. Andersen & R. J. McGaughey, “Light detection and ranging (LIDAR): An emerging tool for multiple resource inventory.”, Journal of Forestry, 103(6), 286–292. https://doi.org/10.1093/jof/103.6.286, 2005.

[11] R. Nelson, H. Margolis, P. Montesano, G. Sun, B. Cook, L. Corp, H.-E. Andersen, B. Dejong, F. P. Pellat, T. Fickel, J. Kauffman, and S. Prisley, “Lidar-based estimates of aboveground biomass in the continental US and Mexico using ground, airborne, and satellite observations,” Remote Sensing of Environment, vol. 188, pp. 127–140, 2017.

[12] E. O. Figueiredo, M. V. N. Doliveira, E. M. Braz, D. D. A. Papa, and P. M. Fearnside, “LIDAR-based estimation of bole biomass for precision management of an Amazonian forest: Comparisons of ground-based and remotely sensed estimates,” Remote Sensing of Environment, vol. 187, pp. 281–293, 2016.

[13] L. T. Ene, E. Naesset, T. Gobakken, T. G. Gregoire, T. Lejeune, and S. Holm, “A simulation approach for accuracy assessment of two-phase post-stratified estimation in large-area LiDAR biomass surveys,” Remote Sensing of Environment, vol. 133, pp. 210–224, 2013.

[14] C. Véga, U. Vepakomma, J. Morel, J.-L. Bader, G. Rajashekar, C. Jha, J. Ferêt, C. Proisy, R. Pélassier, and V. Dadhwal, “Aboveground-Biomass Estimation of a Complex Tropical Forest in India Using Lidar,” Remote Sensing, vol. 7, no. 8, pp. 10607–10625, 2015.

[15] A. T. Hudak, E. K. Strand, L. A. Vierling, J. C. Byrne, J. U. Eitel, S. Martinuzzi, and M. J. Falkowski, “Quantifying aboveground forest carbon pools and fluxes from repeat LiDAR surveys,” Remote Sensing of Environment, vol. 123, pp. 25–40, 2012.

[16] S. C. Popescu, R. H. Wynne, and R. F. Nelson, “Estimating plot-level tree heights with lidar: local filtering with a canopy-height-based variable window size,” Computers and Electronics in Agriculture, vol. 37, no. 1–3, pp. 71–95, 2003.

[17] R. K. Heng, & L. I. M. M. Tsai, “An Estimate of Forest Biomass in Ayer Hitam Forest Reserve,” Pertanika Journal Tropical Agriculture Science, 22(2), 117–123, 1999.

[18] K. Sahin and I. Ulusoy, “Automatic multi-scale segmentation of high spatial resolution satellite images using watersheds,” 2013 IEEE International Geoscience and Remote Sensing Symposium - IGARSS, 2013.