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Assessing the Effect of Crown Slope on Treetops Identification Using LiDAR Canopy Height Model (CHM) and Digital Surface Model (DSM) in a Complex Topography of Tropical Rainforest

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ABSTRACT

Canopy Height Model (CHM) derived from Airborne LiDAR Scanning (ALS) is used for analyzing forest structure which are required the identification of forest stand and its attributes. One of the impacts that can be affected the identification of treetop CHM are crown characteristics such as crown slope. There are only a few studies about the crown slope effect on treetop identification using CHM in tropical rainforest. This paper presents about assessing the impact of crown slope on treetops identification using LiDAR CHM and digital surface model (DSM) in a complex topography of tropical rainforest. The treetop and crown of trees are produced by a Forest tool developed in Rstudio programme which are the ALS surfaces such as CHM and DSM are the main input used in this processing step. The treetop displacements with the crown slope effect in tropical rainforest is quantified and these effect will be assessed using algorithm [$D_V = D_H (\tan\Theta - \tan\psi)$] in order to improve the previous algorithm [$D_V = R (\sec\Theta - 1)$]. Ground data at the field are observed to evaluate the quality of ALS surfaces in producing accurate information of the forest canopy height. The result shows a positive correlation between height of treetops CHM and DSM ($r^2 = 0.996$, tstat<tcrit). Based on the previous algorithm that involved only terrain slope (Θ), horizontal displacement (D_H) between CHM and DSM treetops was highly correlated with vertical displacement, D_V (r2=0.808). However, D_V of treetops using Θ and crown angle (ψ) shows better correlation (r^2=0.924) compared to D_V of treetops using Θ alone (r^2 = 0.720). Therefore, the error determined by involving the crown slope must be considered in CHM analysis before the height information derived by CHM can be used in a forestry application.

Key words : CHM, DSM, LiDAR remote sensing, treetop LiDAR

1. INTRODUCTION

Tropical rainforest in Malaysia requires year round high temperature, plentiful rainfall, dense and lush known as dynamic storehouse of biodiversity on the planet and can be found near the equator [1], holds the most wide-ranging forest in the world with the huge diversity of tree with layered canopies [2]; and crucial role as a carbon sink, which absorbs carbon dioxide from the atmosphere [3]. To maintain the continuity of their useful advantages, an alternative to conduct a research is required for a better understanding about the preservation and conservation of tropical rainforest. Researchers have explored and studied the appropriate methods to find a solution. Remote sensing is a crucial tool offering information for an achievement of sustainable and efficient forest management. Factors such as low spatial resolution due to quality of data, a homogeneous and complex area become a big challenge to classify feature of images [4] and characterized object features on an image. In forestry application, Light Detection and Ranging (LiDAR) has found advantageous such as delineation of tree crown [1], analyses of vegetation cover [5], and deriving forest canopy structure [6].

The mapping of spatial distribution of canopy using LiDAR resulted in capability of this sensor to estimate accurately the tree dimension and canopy structural properties from local to regional and continental scales [7]. LiDAR from airborne and spaceborne gives non-destructive and fast tools for gaining wider coverage area, very useful for monitoring and inventories of vegetation at regional and global scale [8]. Estimating precise location and height of tree has been considered as an important part in providing an accurate data for further analysis such as estimating aboveground biomass (AGB) and carbon stock. LiDAR has their own capabilities in providing point cloud with its attributes (x, y, z) locations from the ground below forest canopy. LiDAR sensor from Airborne Laser Scanning (ALS) has been widely used in extracting structural attributes of forest canopies [9]. Canopy height model (CHM) is required in extracting forest structural attributes such as basal area, stand volume and AGB. However, the impact of slope and crown characteristics on the estimation of tree locations and heights in tropical forests on complex terrain has not yet been investigated or modelled [9].

To detect single tree from LiDAR accurately needs a high resolution of Digital Surface Model (DSM) that appears as the uppermost layer of the forest canopy [10]. LiDAR are capable to characterize horizontal and and vertical structures of forest [11]. A challenge in producing an accurate Digital Terrain Model (DTM) as well as detecting an individual trees and its height occurred due to steep slopes condition in a very dense forest. Appearance of height normalization from DSM and DTM point clouds provide study of errors based on terrain slope cases [12]. The estimation of tree locations before normalization may be a better alternative [9]. LiDAR Surface model is a common method to derive CHM from the upper maximum height above ground obtained from all laser returns of raster cell and identify tree tops as local maxima in the surface model [13]. Crown of each tree can be delineated using watershed segmentation [14]-[15]. However, some information from CHM at lower vegetation is excluded. Therefore, there are approach involved in delineating trees in the most upper canopy layer of CHM or another surface model to analyze all point cloud by k-means clustering, normalized cut, mean shift algorithm or region growing technique [16]-[17].

There is only a few studies related with an effect of slope and crown attributes in estimation of tree locations and heights on complex terrain [9]-[18]-[19]. A study from [18] indicates that there is a decreasing in accuracy of treetop identification during height normalization takes place due to a location of the trees which is on sloping terrain surface. On steep slopes surface, the raw elevation values situated either on the downward or the upward level of a tree crown are height-normalized with parts of the DTM that may be much lower or higher than the tree stem base respectively [20]. The impact of slope-distorted CHMs on treetop identification strongly relies on the tree's crown shape which is mostly specified by its species [18]-[20]. The impact of height normalization on numerous other non-conical crown shapes such as flat or ellipsoidal shapes situated on terrain with a more complex topography must be considered in treetops identification [18]. In addition, an algorithm developed by [9] can be applied to the tree having wider crown radii in tropical forests on slope terrain. [9] found that the error to estimate tree height having a conical crown was effected by the crown angle, crown radius, slope of terrain, while [19] added the factor of crown shape and offset distance to the slope surface. However, more studies are required to determine whether the established models can be used to correct for slope in complex topography since the study [19] was conducted at linear terrain slope of forest terrains.

Programming model is very crucial and useful that incorporate scale and suitable for big data on a machine [21]. To develop the model of CHM analysis, the process having a big data such as LiDAR point clouds must be well handled and improve the decision-making in forestry application. Besides, many of the algorithms for deriving forest information from ALS have been developed in boreal or temperate forests [9]. Therefore, this study aiming the complex topography at tropical rainforest area to study the impact of crown slope on treetops identification managed by programming the input ALS data to estimate the tree height using ALS data in tropical rainforest. The objectives are 1) identifying treetops from CHM and DSM in a complex terrain within a slope terrain factor; 2) estimating difference in height and position of trees from CHM, DSM and ground data; and 3) evaluate the effect of slope on the horizontal and vertical displacements of treetops.

2. MATERIALS AND METHODS

2.1 Study Area

Airborne LiDAR (ALS) represents a small 3 hectare of Berkelah forest located at the central part of Peninsular Malaysia, Pahang at 3°44'25.73" N, 102°57'35.71" E. This tropical rainforest is mixed dipterocarp lowland forests and a type of evergreen tropical moist forest. Berkelah provide the main production of forest where the most areas have been managed for timber production by selective felling. This tropical rainforest is known as a red Meranti forest characterized by a high proportion Shorea species which is categorized under red Meranti group. During 1986 to 1987, this forest was disturbed with tractor-logged activities. Therefore, the vegetation can be classified as a mixed hill dipterocarp forest controlled by Dipterocarpaceae which is the main timber producing tree family [22].

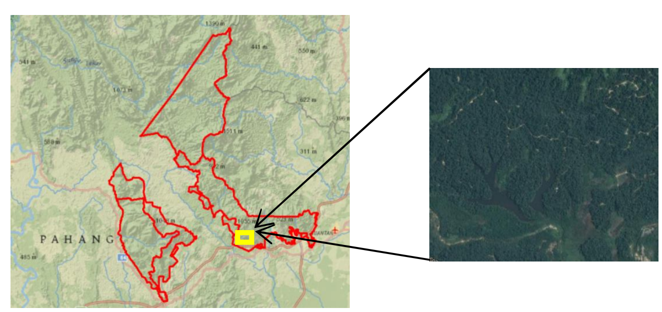

Figure 1: Field plot at Berkelah Forest Pahang.

The research area in Figure 1 covered forest reserve which require a very detailed information of an object due to its condition, e.g. complex structure and difficult to reach. Technique approached (Figure 2) that will be conducted in this study is widely used in previous forest application as well. 53 plots have been conducted around 12.6 meter radius for each plot. The sample plots have designed using Landsat OLI satellite image of 26 June 2016 and Google Earth. Sample plot of coordinate location will be taken. Locations of each tree and the center of each plot was recorded using Garmin GPS, this will be used in matching tree ALS data.

Figure 2 represents the overall framework to conduct the objectives of this study. The ALS data is used to generate the DTM and DSM and a difference between two surfaces is computed in order to produce CHM. The slope terrain is computed in ArcMap software to obtain the value of each cell that are represents the slope angle. Treetop identification and canopy segmentation is generated using variable window filter algorithm while the canopy segmentation is produced by watershed algorithm. D_H and D_V of the treetop; and crown angle is calculated to examine the error in height existing between CHM and DSM, the correlation between D_V with ψ and ϴ; and the relationship of DTM with ground data.

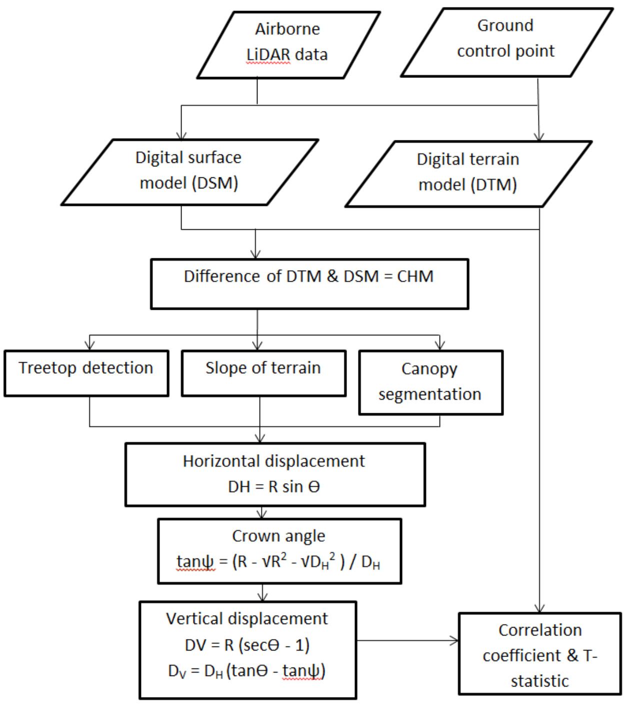

Figure 2: Overall framework represents the objectives of this study.

2.2 Airborne LiDAR (ALS) Data

Airborne LiDAR (ALS) was acquired in 12 November 2014 using Dornier Do228-101 G-ENVR. Leica ALS50-II is used for capturing ALS data. This site captured about 20 lines plus cross in 3 hours 10 minutes duration. ALS data are provided from Airborne Research and Survey Facility (ARSF). The data consists of ALS data with total of 20 flight lines and supplied as Las 1.2 point cloud. In this paper, all the flight lines were combined into one LAS dataset in ArCCatalog tools [23]-[24]. Automatic statistics were calculated for all LAS files to identify the returns, attributes and classification codes provided. The attributes from the statistics indicate the minimum and maximum of return values which is the last return is 4. Therefore, the last return values will be used for generating digital terrain model (DTM) represent the ground or bare earth elevation model which is excluded vegetation, buildings or non-ground objects and the first return values will be used for generating digital surface model (DSM) represents the non-ground objects or forest cover above the ground layer.

2.3. Canopy Height Model

Digital surface model (DSM) and digital terrain model (DTM) are the raster format data and the difference between this two raster will derive the canopy height model [9]. The R-statistic computational is used to explore CHM value for decision making and presentation of the data by producing the boxplot and histogram graph. The cell values in CHM plot are equal to the canopy's height above ground. All outliers will be identified and removed for determining the actual treetops of tree from canopy height model. Therefore, the equation (1) is used to establish CHM:

$$CHM = DSM - DTM \quad (1)$$

Then, the slope terrain is computed using CHM raster using Surface Analyst tool in ArcMap software. ENVI LiDAR is used to generate a 3D viewer in Figure 3 and a cross section (Figure 4); represents the complex terrain of the ALS elevation surfaces. The slope will be categorizes into 5 classes based on the classification terrain complexity [25].

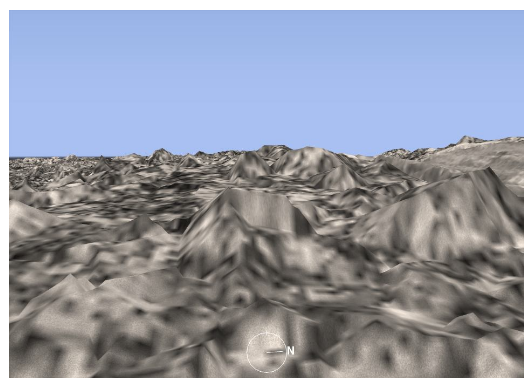

Figure 3: Three dimensional (3D) viewer of ALS elevation in ENVI LiDAR software.

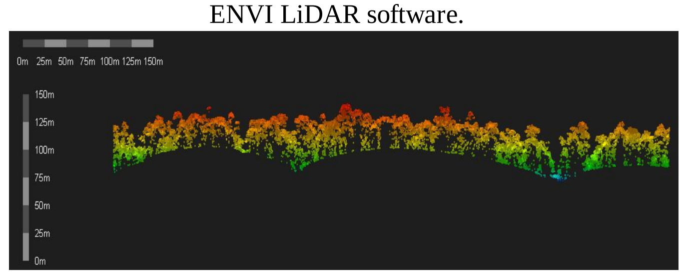

Figure 4: A cross section of ALS elevation terrain.

2.4 Treetops identification

Variable window filter algorithm developed by [9]-[26]-[30] was used to detect treetops in CHM and DSM. This process will be carried out using Forest tools in R-statistic. Any cell that is found to be the highest within the moving window scans from CHM will be tagged as a treetop. The size of the window will change based on the height of the centered cell due to different sizes of crowns. Therefore, dynamic window size will be defined from a simple linear equation involving the height of canopy above ground at the location and return the radius of the search window. The tree with a minimum height of 6 meter and above will be selected in the treetops detection of CHM and DSM. This method will produce treetops with its attribute (spatial coordinates of each treetops, height and radius of window).

2.5 Canopy Segmentation

Crown outline from segmentation process will represent the crown of each tree. Watershed algorithm is applied in DSM and the error will be reduced with marker-controlled segmentation algorithm [13]-[27]-[28]. The result will represent the raster image and will be converted into polygon for further analysis. Crown polygon extracted from DSM is used to mark and manual select the treetop of CHM and DSM that fall into that crown's boundary as shown in Figure 5. Spatial statistics is generated the summarized statistics of tree attributes such as tree count, mean, median, standard deviation, minimum and maximum value of crown area and height of tree.

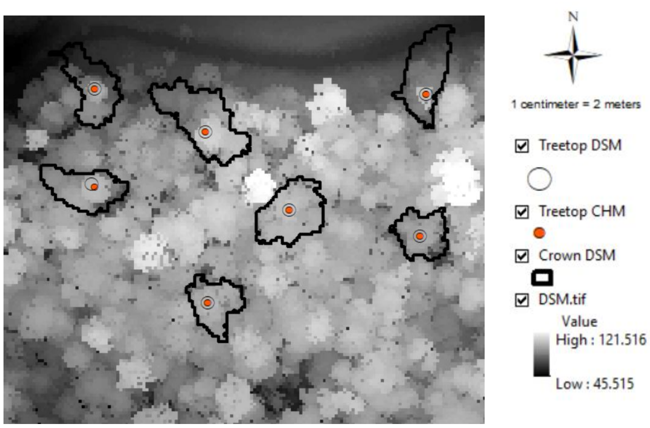

Figure 5: Treetops from CHM are selected within the crown shape and treetops from DSM.

2.6 Horizontal and Vertical Displacement of Treetops

Horizontal and vertical displacement between CHM and DSM treetops were analyzed to determine their relationship with terrain slope and tree crown using correlation coefficient. D_H represent horizontal displacement, vertical displacement (D_V), radius (R), terrain slope (ϴ), and crown angle (ψ) [9]-[29].

$$D_H = R \sin \Theta \tag{2}$$

$$D_V = R (\sec\Theta - 1) \tag{3}$$

$$D_V = D_H (\tan\Theta - \tan\psi) \tag{4}$$

$$\tan\psi = (R - \sqrt{R^2} - \sqrt{D_H^2}) / D_H \tag{5}$$

The algorithm of equation 2 to 4 is applied to quantify the possible errors in the estimation of tree positions and heights from a CHM on sloped terrain. Equation 5 is used to compute the crown angle from DSM. The tree having conical shape of the crown is capable in establishing the correlation between ϴ, crown attributes and displacements in the positions and heights of trees. Statistical analysis such as correlation and t-Test assuming unequal variance (α: 0.05) are applied to study the D_H and D_V of treetops are correlated between each other and ϴ.

3. RESULT AND DISCUSSION

The ALS terrain elevation ranged from 44.92 to 79.769 meter. The maximum ALS terrain slope was 75.8° and the mean slope within a 0.6 meter radius of cells ranged from 2.4° to 64.1°. There were 146 detected trees in DSM that was taller than 6 meter and 76 trees in CHM detected within DSM crown polygon and its treetop. The range for mean height of treetop DSM after terrain normalization was 6.387- 40.969 meter, while the mean height of treetop CHM was 6.435-41.835 meter.

X and Y coordinate of treetop established between CHM and ground control points at the field shows higher correlation coefficient of 0.99 (see Table 1 and Table 2). Then, the height of tree between DSM and CHM is tested and; a positive correlation has found and there was no different between DSM and CHM height (r^2 = 0.996, tstat<tcrit). The estimated height of tree in DSM and CHM would be the same with a terrain slope (ϴ) and a crown angle (ψ) of less than 10°. An error between treetop of CHM and DSM occurred when the angle of slope terrain is bigger than the angle of crown slope. Based on the result obtained after the displacement is performed, the tree height from CHM could be overestimated by approximately 4 meter for a tree having a crown radius of 7 meter, at the terrain slope of 37° and crown angle of 18°.

Table 1: Correlation coefficient for X coordinates point between ground data and ALS data.

	Column 1	*Column 2*
Column 1	1	
Column 2	0.99999478	1

Table 2: Correlation coefficient for Y coordinates point between ground data and ALS data.

	Column 1	*Column 2*
Column 1	1	
Column 2	0.999982723	1

The mean horizontal displacement (D_H) was 0.219-5.157 meter and the mean vertical displacement (Dv) was 0.005-7.371 with 25% of trees in DSM are taller or equal in height to CHM trees. D_H between treetops was highly correlated with their vertical displacement (r^2=0.808). D_H (Figure 6) and D_V (Figure 7 and Figure 8) of treetops were also correlated with terrain slope when its value increasing with terrain slope. Figure 7 shows D_V start to increase significantly at 15° of terrain slope. D_V (Θ) and D_V (Θ and ψ) shows no significance difference between each other (tstat<tcrit). However, Figure 8 indicates that the D_V of treetops using both Θ and ψ shows better correlation (r^2=0.924) compared to D_V of treetops using Θ alone (r^2 = 0.720).

The potential impact of CHM distortion on treetop identification over various terrains has been investigated by [19] and found that the treetop displacement may vary significantly among cases with different terrains. However, the area of study conducted in a linear terrain surface. In this paper, the study is applied in a complex terrain surfaces. [25] has established the classification of terrain complexity factor into 5 classes such as very low (0-5.2), low (5.2-10.6), medium (10.6-16.6), high (16.6-24.1) and very high (24.1-53) complexity of terrain surfaces. In this study, during the selection of treetop between CHM and DSM in canopy segmentation process, the number of treetop detected in 'very low' terrain slope classes is small (5%) compared to 'very high' classes having more (34%) treetops that are match the selection criteria. Another three slope classes shows similar number of treetop detected (20%, 22%, 19%) respectively. It is because the height of tree is set to more than 6 meter for this study area during the treetop extracted process to remove the unwanted grassland and shrubland. Therefore, there are more trees existing at the higher slope terrain indicates that forest structure for this area are compact and difficult to measure height on the ground. These factors give an advantage to crown angle and radius which is capable to establish useful algorithm to model displacement of horizontal and vertical between treetops in order to estimate height of tree.

An error (vertical displacement) occurs when the slope of terrain is more than crown slope. It shows that the tree was located on the steep slope where the angle is wider. Therefore, there is an error and overestimated in height from CHM treetop. Previous study stated that the treetops from DSM were considered to be more accurate compared to treetops extract from CHM due to crown shape of that tree and their position would be maintained in the DSM [9]-[12]-[29]. Therefore, the tree positions and heights from DSM can be represented as the actual values when there are no data from field observation. Hence, DSM can be used to compare the CHM data with the condition where the slope of terrain is lower than crown slope in order to estimate an accurate height of trees. The treetop displacements are closely connected with the terrain slope and crown attributes such as radius, shape and angle. The existence of treetops error relied on the difference between the terrain slope angle and crown angle. Displacement of treetop only appear due to the situation which is crown angle is smaller than the slope angle.

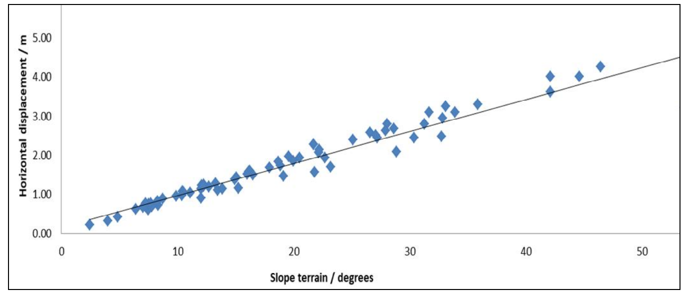

Figure 6: Horizontal displacement between treetops detected in CHM and DSM within the crown of DSM in relation to slope terrain.

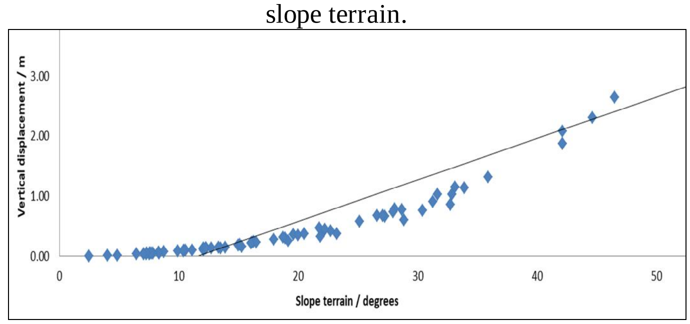

Figure 7: Vertical displacement between treetops detected in CHM and DSM within the crown of DSM in relation to slope terrain using equation (3).

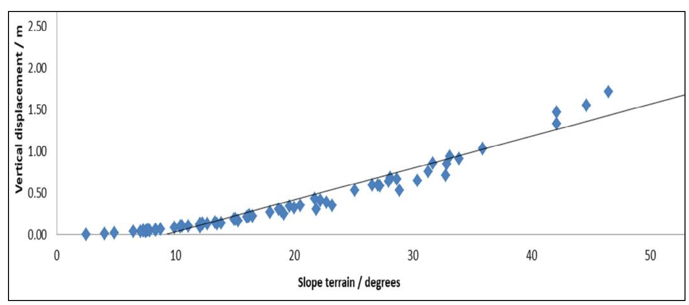

Figure 8: Vertical displacement between treetops detected in CHM and DSM within the crown of DSM in relation to slope terrain using equation (4).

4. CONCLUSION

In this paper, crown slope has found to be one of the angle variables that affected the treetop identification in a complex forest terrain. The variable such as crown radius, slope terrain and crown angle are very useful in quantifying the error of displacement between treetops CHM and DSM. Height and positions of treetop with slope terrain between CHM and DSM are correlated and started to divert when the slope increased but rise again after the crown angle is included in the algorithm. Displacement of error only occurred when the value of angle from terrain slope is larger than the angle of tree crown. Estimation of ALS height comparing to the high quality of ground survey data is considered as a crucial step in order to obtain an accurate observation. In this study, it was hard to measure the height of a single tree. Then, DSM provides an acceptable condition for estimating height due to its ability to detect treetop accurately compared to CHM. The ground data in this study is used to examine the quality of ALS point data using the elevation point on the ground and its coordinates. However, further study of a complex terrain effect on treetop identification is required since this paper only focusing on crown angle impact.

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