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Original article

Airborne LiDAR for Estimating Aboveground Biomass in Dry Evergreen Forest : A Site of Khao Yai National Park, Thailand

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ABSTRACT

The objective of this study was to utilize the advanced LiDAR technology and high resolution aerial photography in conjunction with an allometric and regression model to determine the value of coefficient of determination between the tree height estimated from LiDAR and field-measurement. The study covered an area of 22.5 square kilometers of Khao Yai national park, in Hintang sub-district, meung Nakhorn Nayok district, Nakhon Nayok province, Thailand. The results of the study indicate that tree heights generated from LiDAR data can be used to calculate the diameter at breast height (DBH) using a regression model and to estimate the aboveground biomass using allometric equations for a dry evergreen forest. Through the results, we concluded that the aboveground biomass can be categorized into three levels: a high level (more than 1,000 kg of aboveground biomass) estimated for 36.8% of the study area, moderate level (500 – 1,000 kg of aboveground biomass) estimated for 23.4% of the study area, and low level (under 500 kg of aboveground biomass) estimated for 39.8% of the study area. Using the LiDAR and high resolution aerial photography, it is possible to estimate the aboveground biomass of the crown cover with a high level of accuracy in a real world setting. The results prove the potential of the LiDAR technique in accurately estimating the aboveground biomass of a multi-layerd and complex forest structure such as a dry evergreen forest in Khao Yai national park, as indicated by the prediction accuracy of the regression model . The authors must inform the RMSE and percentage of RMSE for aboveground biomass estimations.

Keywords: forestry, aboveground biomass, allometric model, lidar, carbon stock potential forcasting

INTRODUCTION

Project Overview

An ever increasing size of industry and agriculture has resulted in an increase in logging and deforestation. Deforestation has a considerable impact on the environment such as global warming, climate change, weather variation, human and animal health problems, and increase in mean sea levels. There are many factors that drive environmental change which include population growth and high fuel consumption due to an increased usage of vehicles. These factors are contributing to the release of toxic greenhouse gases into the air, which are primarily responsible for global warming, resulting in increased levels of carbon dioxide (CO_2). Therefore, various international organizations are collaborating to reduce global warming and prevent its negative effects. The United Nation (UN) held a conference which was attended by countries concerned and directly affected by this problem. In 1997, The Kyoto protocol was implemented in Kyoto, Japan. This protocol requires member states to find systems or measures to reduce greenhouse gas emissions. Such mechanisms are called clean development mechanisms (CDM) that help reduce emissions and ensure a sustainable development. The CDM project is a baseline for any projects to reduce the sources of greenhouse gases. One objective of the CDM project is to provide financial assistance or funding support for developing countries. Hence, most CDM projects are focused on reducing greenhouse gas emissions from industrializing or developing countries.

Tropical rain forests are the primary type of forests found in Thailand. However, the major forest type in the study area was evergreen forest. This forest type is composed primarily of tree species that are important for ecology and carbon stocking sources in this region. The objective of this study was to estimate aboveground biomass using an allometric model with LiDAR data. The estimation technique was based on the method of the verified carbon standard (VCS). In this method, the measurement of data to determine a baseline level must take place not more than 5 years after the project start date. This study examined fixed area plots using primary data from fieldwork in 2015 and secondary data from a digital terrain model (DTM) and an orthophoto that were generated in 2012 as the baseline data. After planning and data preparation was completed, this study used the VCS method to develop an allometric equation for the evergreen forest. The last step was to estimate the carbon stock in the aboveground biomass for each individual tree in the study area.

This results from the study will serve as a knowledge base and high quality benchmark for other researchers who are interested in estimating carbon measurements using an allometric model or in the methodology for estimating the aboveground biomass for a dry evergreen forest. The results from this study can serve as a baseline for estimating the aboveground biomass using LiDAR technology to validate the certification in carbon market, in order to help get funding or financial support for REDD+ projects.

Objective

To estimate the aboveground biomass using tree height measurements from Airborne LiDAR data and allometric model for the estimation of aboveground biomass of dry evergreen forest in the study area located in Khao Yai national park**.**

Study Area

The study area is located at 101° 19′ 40.05″ north longitude and 14° 21′ 4.58″ east latitude in the Khao Yai national park, which covers approximately 22.5 square kilometer. The number of sample plots in the field were calculated using Winrock International (MacDicken, 1997). Field data was taken during February 2014 to the end of August 2016. A total of 40 plots were set up, with the size of each plot being 50 meters x 20 meters.

MATERIALS AND METHODS

Materials

The materials and instruments used for collecting the spatial data for this research are described as follows:

Primary data was collected in the sample plots from February 2014 to August 2016.

1. Tree girth at breast height (GBH) was recorded in centimeters.

2. Tree height was recorded in meters.

3. Canopy area was recorded in square meters using a polygonal format generated by the spatial processing tools available in ArcMap software. .

Secondary data:

1. Airborne LiDAR data was collected from the study area in 2012 in the Laser Airborne Scanning (LAS) format, with a spacing of 1.5 meters and a vertical accuracy of 0.5 meters.

2. A high resolution orthophoto of the study area was created from the airborne photogrammetry in 2012.

3. Data related to the type of forest in the study area was acquired from The Department of National Parks, Wildlife and Plant Conservation of Thailand (DNP).

4. The dry weight index of stems (W_s), branches (W_b), and leaves (W_l) for dry evergreen forest types (Viriyabancha *et al.*, 2002) were calculated using allometric equations.

The tree measurement data collected for this research was obtained without cutting down any trees. The data was collected from surveys conducted in the sample fields.

Methods

Before starting this research, it was important to review and study the research papers related to the carbon inventory of the dry evergreen forests in order to understand how to calculate the biomass from an allometric equation. Other important reference documents were the research papers and articles related airborne LiDAR surveying using forestry and Digital Surface Model (DSM) generating methodology.

A workflow chart was prepared as a guide as shown in Figure 1. Following this workflow chart, plans were made to measure the tree height in a 22 square kilometer study area of Khao Yai National Park, using Airborne LiDAR, in September 2012.The LiDAR data was the processed as multiple points, including tree heights, using the Leica Photogrammetry Suite (LPS) software. After the tree heights were prepared, tree heights and DBH values were determined from 40 sample fields to study the relationship between tree height and DBH. Then a simple linear regression fit was made for predicting the DBH values for all trees in the study area from the known tree height values collected through LiDAR. Data for all the trees was extracted using the spatial processing tools from ArcMap software, described in Figure 9. When the tree height and DBH values was being prepared, this data was used in conjunction with an allometric model for a dry evergreen forest type to calculate the above ground biomass (ABG). Finally, an ABG map was constructed to classify ABG volume into three different intervals, i.e., ABG less than 500 kilograms, ABG between 501 to 1,000 kilograms, and ABG more than 1,000 kilograms.

Predictions about the data gathered during fieldwork were made using various models. Primary data was collected from sample plots using the following 9-step process:

1. Well defined trees were selected which can be identified from a Digital Orthophoto in order to mark their original positions in the sample fields.

2. 40 sample fields of 50 meters x 20 meters size of each were set up according to Winrock's sample field calculation. The sample fields were evenly distributed to cover a study area within the dry evergreen forest.

3. A grid was constructed by masking a number on rope after a distance of 1 meters. The rope was stretched from its original position such that 20 meters in the northern direction was the Y axis and 50 meters in the west direction was the X axis.

4. Only those trees were selected which had a DBH > 4.5 centimeters and were alive.

5. Tree position was measured in the original sample fields, and recorded as x and y distance through the masking tape as a label tag and wrapped on the tree.

6. GBH of a tree was measured in centimeters by a measuring tape, and the GBH value with a masking tape as a label tag and wrapped on the tree.

7. The tree height was measured in meters using a Nikon Forest Pro, 3 times per tree, and an average tree height was calculated from the 3 height values.

8. The tree crown cover area was measured by collecting directional distance data in 4 directions (North, South, East and West) from a tree stem to the tree crown edge. A tree profile was drawn to compare with the high-resolution orthophoto to match the

tree position inside the sample fields with the orthophoto.

9. Individual tree photos were taken with a label tag.

In this research, the ABG volume in the study area was the final output as a high resolution carbon map. This method can calculate the biomass by sampling tree dimensions, but the dimensions of all trees in the study area are not known in actuality. All trees in the study area have two known values, the tree height and canopy area from the LiDAR Data, while the DBH was the unknown value. The regression model was used to calculate the DBH for each tree in the study area and an allometric equation was used to calculate the biomass in study area.

After collecting the tree position and dimensions, these positions were plot onto a map by using the relative X and Y coordinates from the sample field. This was done by mapping each tree and its dimensions onto a spreadsheet for generating a regression model to calculate the coefficient of determination between the values of each dimension.

This model was used to examine the relationship between tree dimensions from sample fields as the independent variable and tree dimension from LiDAR data as the dependent variable. After performing the analysis, the regression statistics can be used to predict the dependent variable when the independent variable is known. Regression goes beyond correlation as it adds prediction capabilities to the model thus constructed.

The regression line is a plot of the predicted value of the dependent variable for all values of the independent variable. It is the line that minimizes the squared residuals. The regression line is the one that best fits the data on a scatter plot.

Using the regression equation in this research, the dependent variable was predicted from the independent variable. The independent variables are the tree height, tree DBH, and tree crown cover from sample field and others data sources are the tree height and tree crown cover from LiDAR data. The dependent variables are the tree DBH from the LiDAR data. A simple linear regression equation can be mathematically written as

$$Y = a + b(X), \quad (1)$$

where X is the explanatory variable and Y is the dependent variable. The slope of the line is b and a is the intercept (the value of y when x = 0).

The slope of the regression line (b) is defined as the rise divided by the run. The Y intercept (a) is the point on the Y axis where the regression line would intercept the Y axis. The slope and Y intercept are incorporated into the regression equation. The intercept is usually called the constant and the slope is referred to as the coefficient. Since the regression model is usually not a perfect predictor, there is also an error term in the equation. In the regression equation, Y is always the dependent variable and X is always the independent variable.

The coefficient of determination between two variables in a data set equals to their covariance divided by the product of their individual standard deviations. It is a normalized measurement of how the two are linearly related. The quantity R^2, called the linear coefficient of determination, measures the strength and the direction of a linear relationship between the two variables and is given as

$$ {}^{2}\sqrt{n(\Sigma x^2) - (\Sigma x)^2} \quad \sqrt{n(\Sigma y^2) - (\Sigma y)^2} \Big]_2 $$

After predicting the DBH value for any tree in the study area, the allometric equation is used to calculate the aboveground biomass for any tree. The allometric equations used in this research are for the specific forest types (Viriyabancha *et al.*, 2002) as indicated below:

For dry evergreen forest

$W_s = 0.0509 * DBH^2 * Ht^{0.919}$,

$W_b = 0.00893 * DBH^2 * Ht^{0.977}$,

$W_l = 0.0140 * DBH^2 * Ht^{0.669}$,

where W_s is stem biomass in kilogram estimated of the dry evergreen forest. W_b is branch biomass in kilogram estimated of the dry evergreen forest and W_l is the leaf and branch biomass in kilograms estimated of the dry evergreen forest. Ht is tree height estimated from the LiDAR measurement.

The allometric equation used in this research can be reformatted into a final equation of the form:

Above ground biomass = $\Sigma W_s + \Sigma W_b + \Sigma W_l$.

The last method in this research is to collect height data using LiDAR measurement for trees in the study area and use the height so obtained in the equations using GIS technical to extract the highest values from the LiDAR data. The method used in this part can be outlined as follows:

1. Preparing LiDAR cover study area. The projection of data must be in UTM 1984 Zone 47N and in meters unit with the vertical system from mean sea level in meters unit.

2. Using ArcMap software to display LiDAR data in the study area.

3. Area base conceptual is a main thought to collecting LiDAR height from study area. The basal area tool was developed to extract the canopy shapes from LiDAR data. This tool is in the model builder of ArcMAP software.

4. Using basal area tool to extract canopy shapes. The logic tool is explained in Figure 2.

4.1 Transforming 1 meter of pixel size to 3 meters of pixel size using raster resampling.

4.2 Transform inverse pixel value of raster file to negative value. As such, this method will transform a higher value to a lower value. The flow direction processing from the hydrology toolbox is used to calculate and display the output as an area of canopy shape.

4.3 Any canopy shape has only one height value obtained from the LiDAR. The basal area tool is able to select the highest value from LiDAR inside the canopy shape by using ArcMap 10.2 spatial join tool.

4.4 Calibration results of canopy shape from basal area tool with canopy from sampling area. The research focusses on calculating the area base, but the main aim is estimating the aboveground biomass in study area by predicting the DBH from LiDAR data in sample plots located inside Khao Yai national park. Therefore, the number of canopy shape from the tool must approximate to the number of canopy shape determined from the field sampling area.

5. After that, the tree height values from LiDAR data were collected for any canopy shape using the basal area tool. Used DBH and LiDAR tree height relation, from equation (3), to replace any LiDAR tree height value in height LiDAR for predicting the DBH. Then used any height LiDAR and predicted the DBH to substitute into the final allometric equation (4) for calculating the aboveground biomass of each tree.

6. Use ArcMap to map the value of forest aboveground biomass in the study area using the symbology function to describe the level of aboveground biomass in kilogram.

RESULTS AND DISCUSSION

After taking X and Y values from the tree height and tree DBH regression equation, we found that the coefficient of determination (R^2) was 0.6715 as indicated in Figure 3.

$$R^2 = 0.6715$$

Coefficient of determination between DBH and Tree height in the sample fields

The coefficient of determination, as calculated from the linear regression equation comparing the tree height and DBH measured in the sample fields, was 0.6715. The result is close to +1. It means that 67.15% of the tree height data obtained from the sample fields and LiDAR were in agreement. In other words, the relationship between tree height in the sample fields and tree DBH from the sample fields variables are related such that as the values for tree height in sample fields increases, tree DBH value from the sample fields also increases.

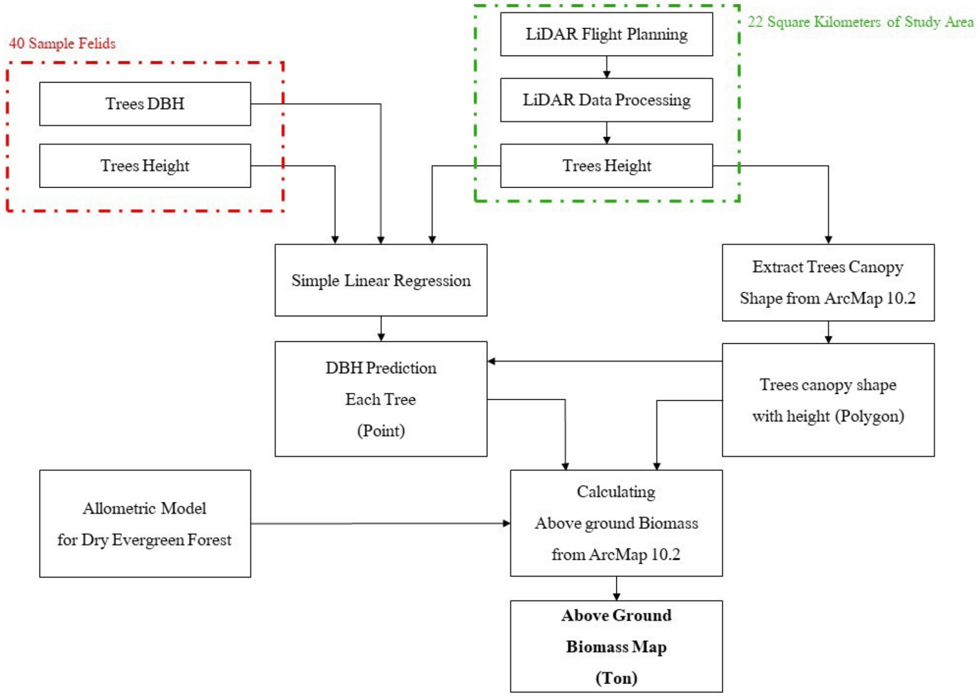

Figure 1 Study work flow.

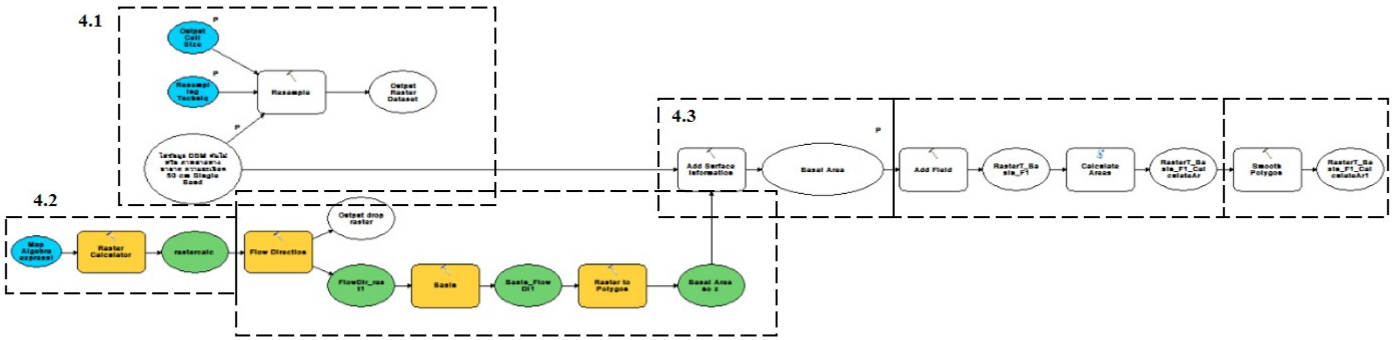

Figure 2 Trees shape extraction logic in Model Builder, ArcMap 10.2.

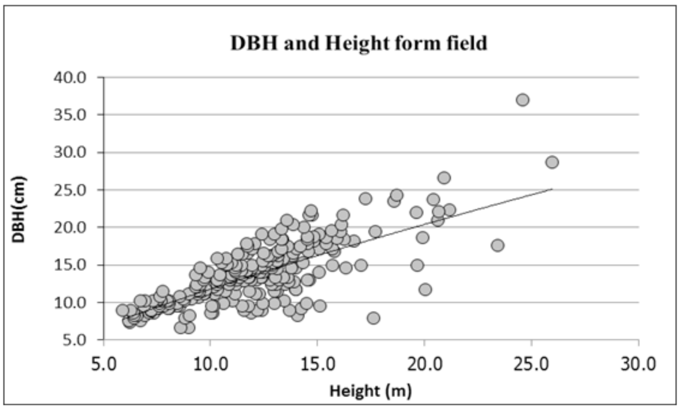

Figure 3 Relation betweem the tree height and DBH in the sample fields.

$$Y = 0.7185X + 4.9663,$$

$$Y_{dbh} = 0.7185X_{field} + 4.9663, \quad (2)$$

$$R^2 = 0.6715,$$

where Y_{dbh} is the DBH value in centimeters and X_{field} is the tree height obtained from the field measurement in meters.

The Coefficient of determination between the tree height in sample fields and tree height from LiDAR

The coefficient of determination from the linear regression equation which compared the tree height measured in the sample fields and tree height from LiDAR data was 0.9754. This result is close to +1 indicating that 97.54% of the mean tree height data obtained from the sample fields and tree height data from LiDAR data are in agreement. In other words, the relationship between tree height in sample fields and tree height from LiDAR data is such that as the values of tree height in the sample fields increases, the values od tree height from LiDAR data also increase (Figure 4).

$$Y = 0.\ 0.9948x + 1.8675,$$

$$Y_{field} = 0.\ 0.9948X_{LiDAR} + 1.8675, \quad (3)$$

$$R^2 = 0.9754,$$

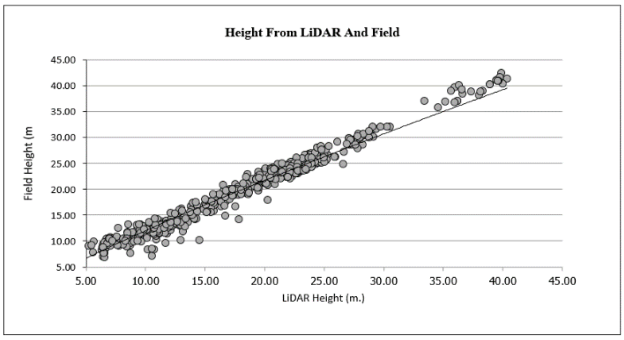

Figure 4 Relation from tree height from LiDAR and tree height in sample fields.

where Y_{field} is tree height obtained from field in meters and X_{LiDAR} is tree height obtained from LiDAR in meters.

From Equations (2) and (3), we can eliminate X_{LiDAR} and combine the two equations into a new formula by using algebraic manipulation. In this research, Y_{dbh} is the predicted DBH output value used to calculate the aboveground biomass. Y_{field} is an independent variable or input used for prediction. It can get be obtained from LiDAR data by using GIS methods. X_{LiDAR} is relative between Y_{dbh} and Y_{field}. It is used to transform the 2 equations (1) and (2) to a single equation for predicting the DBH value using LiDAR height (3) as indicated in the equation below:

$$\left.\frac{}{0.\ 0.9948}\right]\right] \quad (4)$$

Quantification of canopy shape

The density of Laser Airborne Scanning (LAS) in this research is 1.5 meters of spacing which was not enough to define the actual shape of tree canopy in the study area. The area base approach was practiced to approximate the number of trees for an estimation of forest inventory (Naesset, 2004). The area base approach was fixed as a pixel size relative to the tree. On the other hand, this research did not sample trees size less than 3 meters in pixel size as the canopy measured from the sample field data had a canopy dimension of the smallest tree, in the 4 directions, as 1 meters each in north, south, east, and west. Thus, when plotting canopy shape in the map, 1 pixel represents a tree, 1 meters from tree position to the north, 1 meters from tree position to the south, 1 meters from tree position to the east, and 1 meters from tree position to the west. The total pixels covered by the smallest tree was 9 square meters or 3 meters of pixel size as indicated in Figure 5. This research used the area base approach to determine the size of trees which are bigger than 9 square meters or 3 meters in pixels. The size of a tree was represented as canopy shape since a canopy can be defined from the DSM after conversion from LAS file. This canopy shape is closer to a real canopy shape to represent any tree and thus, increase confidence in the estimates of aboveground biomass. Thus, the best algorithm to generate canopy shape with a 1.5 spaced LAS file in this case is the cubic convolution resampling method and 2 meters x 2 meters in pixel size to resample from 1 meters x 1 meters pixel size as shown in Figure 6. The number of tree polygons which were spatial processed by the ArcMap 10.2 Software was 602,730 trees.

Result of aboveground biomass

The result of aboveground biomass deduced from ABG mapping indicates that the dry evergreen forest stratum in the study area has a total aboveground biomass of 460,448,432 kilograms or 460,448.4 metric tons, while the number of trees is 602,730 as shown in Table 1. Every tree is assigned a latitude, longitude, and aboveground biomass value, and can be used to represent a high resolution carbon mapping to describe the level of aboveground biomass in the study area with 3 levels. The first level is assigned to trees with under 500 kilograms of aboveground biomass, which covered 12.6 square kilometers (36.8%) and is displayed with green color. The second level is assigned to trees with 500 – 1,000 kilograms of aboveground biomass covering 8 square kilometers (23.4%) and is displayed with yellow color. The third level is assigned to trees with an aboveground biomass of more than 1,000 kilograms and covered 13.6 square kilometers (39.8%), displayed with red color as indicated in Figure 13. The GIS technique used to represent a 3 dimensional view of the aboveground biomass levels with topography data derived from Digital Terrain Model (DEM) which was used to classify the ground level in the LiDAR data and is shown in Figure 7.

Figure 5 Smallest of tree size with an area of 9 square meters or 3 meters in terms of the number of pixels.

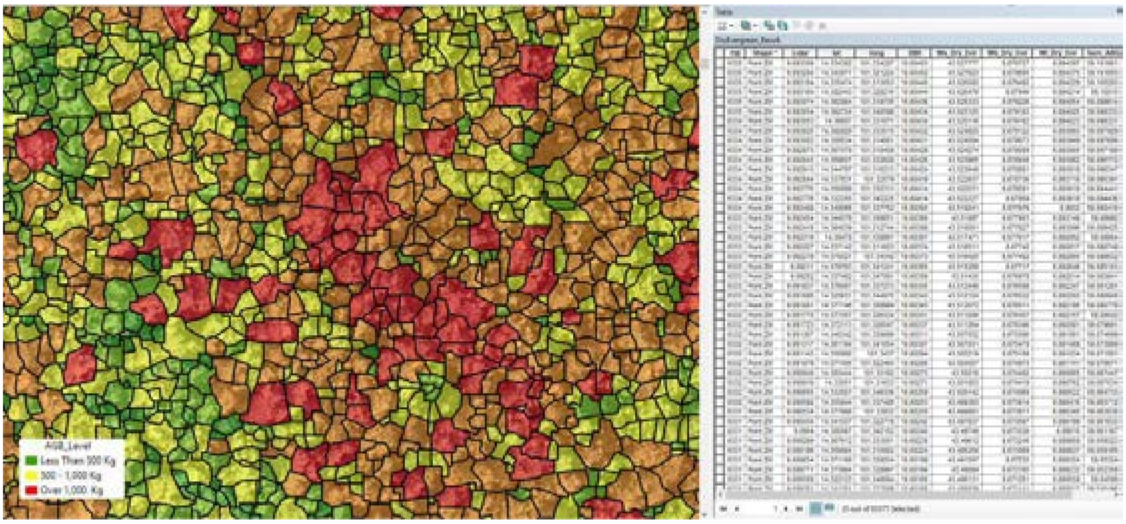

Figure 6 The best fit algorithm to generate the canopy shape.

Table 1 The estimated aboveground biomass in study area.

Total tree	Area (km^2)	Forest type	Ws (t)	Wb (t)	Wl (t)	Aboveground biomass (t)
602,730	22.5	Dry evergreen forest	317,314	55,670	87,464	460,448

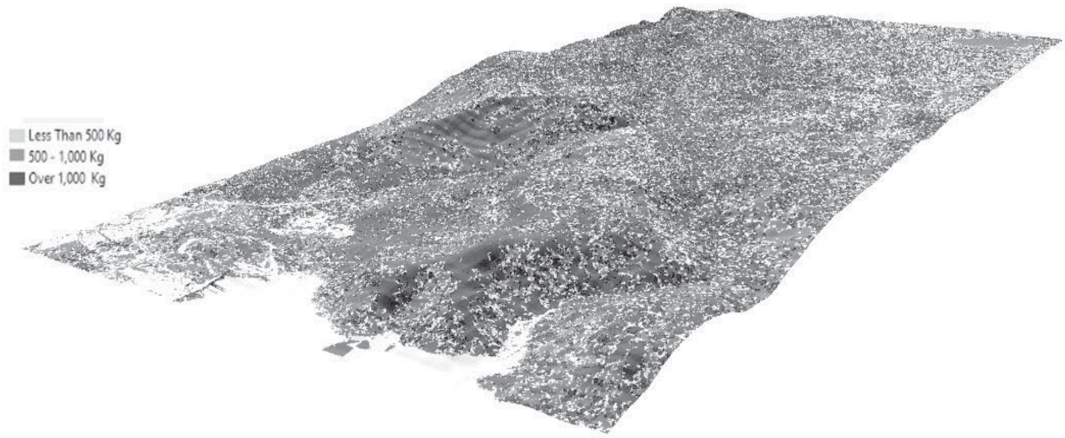

Figure 7 The estimated aboveground biomass indicated as carbon mapping with 3 levels of biomass value.

CONCLUSION

LiDAR data and high resolution aerial images can be used in conjunction with the regression modelling and GIS techniques to determine an allometric equation to estimate the aboveground biomass in the study area. The accuracy of DBH as predicted from a 1.5 meter ground spacing and 40 sample plots is approximately 67.15% in agreement of the total DBH data. The sample fields in this study area can be increased to include more field plots or higher tree population to increase the confidence level of the estimation.

A suitable allometric equation for estimating the aboveground biomass was used along with an allometric equation of the specific forest type (Viriyabancha *et al.*, 2002). In this study, we did not used destructive techniques of wood cutting and drying process for the biomass estimation. The aboveground biomass was used to construct a carbon mapping with 3 levels of above ground biomass level with trees having less than 500 kilograms biomass covering 12.6 square kilometers (36.8%), 500 – 1,000 kilograms covering 8 square kilometers (23.4%), and over 1,000 kilograms covering 13.6 square kilometers (39.8%).

Recommendations

The generation of canopy shape needs a high density in the LAS file to process in the basal area tool. The algorithm in this tool works very well with curved surfaces. That is an attribute of high density LAS file. Ideally, the 0.2 meter LAS density or 5 point per 1 square meter is sufficient to extract the canopy shape by using the basal area tool. Airborne Laser Scan (ALS) configuration should have a narrow field of view (FOV) and high pulse rate for generating a high density LAS file to have a higher accuracy in the forest inventory.

Allometric equation in this research used the equations recommended for evergreen and deciduous forests because the hypothesis is to calculate the above ground biomass in these 2 type of forests using LiDAR data while focusing on an area base approach. Thus, previously reported allometric equations (Viriyabancha *et al.*, 2002) for these 2 forest types were used to calculate the aboveground biomass. This research focused on the major forest type in Khao Yai national park, which is a dry evergreen forest type. The study area was planned so as to collect data in sample fields only in the dry evergreen forest type. While the Khao Yai national park also has another forest type which covers approximately 25 % and is classified as a mixed deciduous forest. This forest type should be used to collect sample data to have a complete picture of the estimated above ground biomass in the Khao Yai national park.

The statistical analysis of height metrics such as maximum height, mean height, and percentiles of canopy height calculated from the LiDAR point cloud data is important for estimating the individual tree height, and consequently estimating the plot-level aboveground biomass. If possible, the authors should show the structural and image metrics of LiDAR point cloud derived from some horizontal lines of some sample plots.

Additionally, the authors should conduct Pearson's correlation test between field reference data and LiDAR-estimated aboveground biomass, and then calculate the relative root mean square error (RMSE) and the relative RMSE for the aboveground biomass estimates at the forest stand level.

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