ABOVE GROUND BIOMASS (AGB) ESTIMATION OF COCONUT (*Cocos nucifera*) and MANGO (*Mangifera indica*) TREES FROM LIDAR DERIVATIVES USING REMOTE SENSING TECHNOLGY

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KEY WORDS: CHM, nDSM, tree height, DBH and crown area

ABSTRACT

This paper demonstrates the utilization of LiDAR derivatives for above ground biomass (AGB) estimation of coconut (*Cocos nucifera*) and mango (*Mangifera indica*) crops in Butuan City, Agusan del Norte, Philippines. The estimation of potential biomass of coconut and mango crops is important for various applications such as yield prediction, nutrient management and analysis of carbon sequestration. With the aid of LiDAR Technology, feature extraction is more precise and accurate. Prior to estimation, classification of image-objects was done by developing rule sets in eCognition software. LiDAR point cloud data was used to generate LiDAR derivatives such as Normalized Digital Surface Model (nDSM), Digital Surface Model (DSM) intensity and Canopy Height Model (CHM). The certain class vegetation objects were pre-classified into classes such as High Elevation Group (HE) of which coconut and mango trees belong, Medium Elevation Group (ME) and Low Elevation Group (LE) according to heights in the LiDAR nDSM that also contained sub-classes. Tree height and crown area as the parameters used for AGB estimation could be determined in the eCognition environment. Actual measurement of coconut and mango diameter at breast were conducted at the field using stratified sampling method. Based on the results, this study shows 94.36% overall accuracy of classification of maps resulted to a significant estimation of above ground biomass.

1. INTRODUCTION

Agriculture continues to be a major source of gross domestic product, total employment, and livelihood of the rural sector. Mindanao holds high prospects for agricultural development in the country. It is considered the country's food basket, supplying over 40 percent of the country's food requirements and contributing more than 30 percent to national food trade. However, food security is a big challenge in the country due to adverse effect of climate change to agriculture and the food demand of the increasing population. Hence, measuring biomass in crops is important for yield prediction, nutrient management and analysis of carbon sequestration. Monitoring and estimation of biomass of the agricultural crops are important for management practices such as irrigation, pest and control and fertilizer application.

Live tree biomass estimates are essential for carbon accounting, bioenergy feasibility studies, and other analyses. Several models are currently used for estimating tree biomass. Each of these incorporates different calculation methods that may significantly impact the estimates of total aboveground tree biomass, merchantable biomass, and carbon pools (Zhou and Hemstrom, 2009). Tree allometry is a statistical tool to relate some fairly easy to measure parameters of trees like DBH to such parameters which are often more difficult to assess. To obtain such relationships detailed measurements on a small sample of typical trees are made and then relationships are worked out such that they permit extrapolations and estimations of a host of dendrometric quantities on the basis of a single (or at most a few) measurements. This approach eases out difficult field work and enhances the speed of data collection and estimating tree biomass (Ganeshamurthy et.al, 2016).

Also, forest biomass is an essential factor in environmental and climate modeling. Quantifying the amount of biomass within a forest stand is necessary for property managers to make informed decisions about the value and use of their forested land. Light Detection and Ranging (LiDAR) is one of the most promising remote sensing technologies for estimating various biophysical properties of forests. LiDAR provides the most accurate measurements of terrain elevation and vegetation height; this accuracy holds even on sloped terrain or in dense forests (Qisheng et.al, 2013).

Remote sensing using LIDAR has been gaining popularity. Airborne altimetric light detection and ranging (LiDAR) introduces the possibility of discrete three-dimensional analysis of vegetation and terrain features. This active sensor emits laser pulses over a swath of terrain and records the intensity and round trip travel times of the returning pulses, which are then converted into range measurements (Arroyo et al., 2010). As cited in the works of Arroyo et al., the potential of airborne laser scanning to retrieve structural attributes of forest communities has been widely illustrated (Clark et al., 2004; Lefsky et al., 2001; Persson et al., 2002; Popescu and Zhao, 2008; Suarez et al., 2005; Zimble et al., 2003).

Moreover, with the aid of LIDAR Technology, accuracy is evident and acknowledged by many government and commercial sector. Thus, the need for precise and accurate extraction of data as a baseline for potential above ground biomass estimation high value crops in Butuan City is vital. And this will provide more reliable information for decision making regarding crop vegetation. This will also offer new windows of opportunity for future research and development related with crops.

1.1 Objective

The main objective of this project was to estimate above ground biomass of coconut (*Cocos nucifera*) and mango (*Mangifera indica*) trees from LiDAR derivatives. Specifically, the project aimed to: (1) classify the agricultural resources in Butuan City using the rule set developed (Learned SVM) in Ecognittion; (2) extract the mango and coconut features from the classified objects; (3) conduct diameter at breast and height measurement of mango and coconut trees; (4) develop allometric equation from the collected data using statistical analysis tool; and (5) produce map for the above ground biomass distribution of mango and coconut trees in Butuan City.

2. METHODOLOGY

In order to classify and estimate the above ground biomass of coconut and mango trees in Butuan City, Agusan del Norte, Philippines the following process shown in Figure 1 was employed.

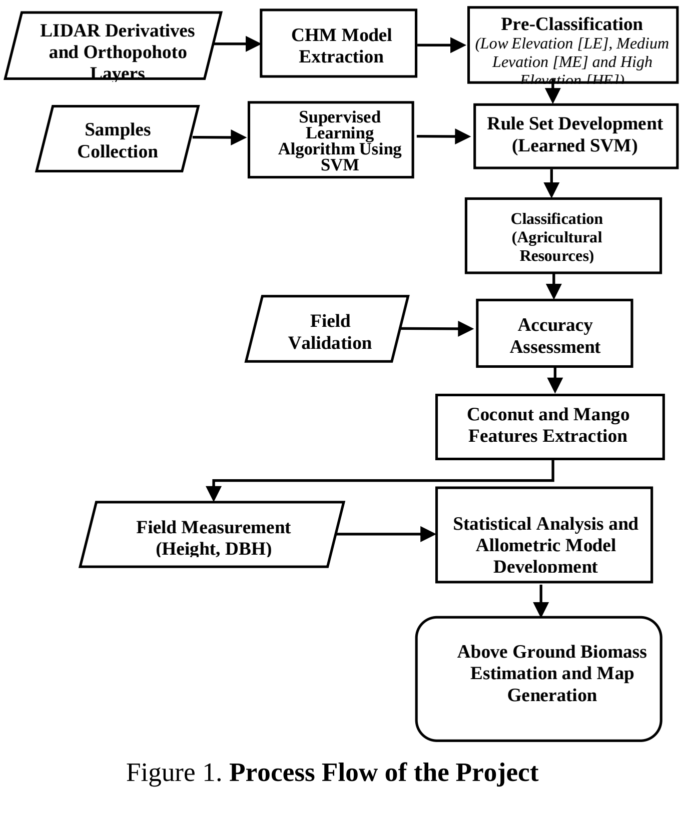


Figure 1. **Process Flow of the Project**

2.1 Image Classification

In the classification of high value crops, pre-processed LiDAR data and colour aerial imagery (orthophoto) of Butuan City were the remotely sensed datasets used in this project. Both of these datasets will be obtained from the UP-DREAM program. Prior to classification, the object was segmented first for object-based image analysis. Segmentation was the process wherein adjacent pixels were grouped together based on their homogeneity thereby creating meaningful “objects”. These objects were then subjected to classification. Both segmentation and classification was done with ease through different algorithms in eCognition (Trimble eCognition Reference Book, 2014). Object-based classification was done through user-defined rule-sets. However, different classes of objects weren’t separable by direct thresholding one feature at a time (Japitana, et.al. 2015).

2.1.1 Supervised Learning Algorithm using SVM and Rulesets Development

A Supervised learning algorithm called SVM (Support Vector Machine) was used to classify land features in the image. The LiDAR derivatives (nDSM, DSM intensity), Green Ratio, and EVI were used as features for developing the SVM model. However, SVMs also suffer from parameter assignment issues that can significantly affect the classification results. More specifically, the regularization parameter C in Linear SVM has to be optimized to increase the accuracy. We perform the optimization procedure in MATLAB. The learned hyperplanes separating one class from another in the multi-dimensional feature space can be thought of as a super feature which will then be used in developing the rule set in eCognition. Rulesets were developed which employed optimization using MATLAB. These were based on roundness, compactness, area, height, height standard deviation and asymmetry of the feature class (Candare, et.al, 2015).

2.2 Field Validation and Accuracy Assessment

To assess the accuracy of the classified land cover using the general rule sets developed, field validation surveys were conducted to verify the actual land cover existed in the area. Prior activities involved for validation were as follows: (a) selection of training/validation points, (b) digitizing of road routes, (c) field guide map creation, and (d) actual field validation surveys. Using the validated points collected during field validation surveys of the project, the resulting classification underwent accuracy assessment through post classification confusion matrix in ENVI.

2.3 Coconut and Mango Feature Extraction

From the classified land cover, coconut and mango features were extracted in the eCognition environment and converted it to shapefile for GIS application. Coconut and mango tree heights and crown area were among the attributes extracted using eCognition software as one of the parameters in the estimation of the above ground biomass. Moreover, the extracted features were used as the basis in the identification of the sampling site based on the area distribution of each crop using stratified sampling method.

2.4 Field Measurement

After extraction and identification of sampling site, field measurement was performed. There were five (5) sampling points per crop visited with a 20m x 20m field layout. For DBH measurement, measuring tape was used. For mango, DBH was measured at 30 cm from the ground since most of the mango plantations were grafted type while for coconut, DBH was measured at 130 cm from the ground. Moreover, coconut and mango heights were measured in the field using Range Finder. In this study, there were a total of one hundred (100) numbers of observations of each crop subject for statistical analysis.

2.5 Statistical Analysis

The collected data were analyzed using Regression Analysis using 95% level of confidence to generate allometric model for DBH using tree heights. The allometric equation was used to determine the DBH of each feature extracted where height is known.

2.6 Above Ground Biomass Estimation and Map Generation

To estimate the potential above ground biomass of coconut and mango trees extracted in the eCognition environment from the LiDAR derivatives, the allometric equation for trees with rainfall greater than 400 mm/year in the lowlands developed by Brown (1997) was used as shown below.

$$AGB = 21.297 - 6.953 * DBH + 0.740 * (DBH^2)$$

Moreover, the distribution of potential above ground biomass of coconut and mango trees (kg) in Butuan City, Agusan del Norte, Philippines was illustrated using GIS technology.

3. RESULTS AND DISCUSSIONS

3.1. Classification of Resources and Accuracy Assessment

The developed ruleset algorithm from the learned optimized parameters in SVM was applied in eCognition software using the different LiDAR derivatives and orthophoto layers. The output parameters were used as threshold that separate between a class to the other class (i.e. mango to coconut or vice versa, etc.). Based on the result as shown in Figure 2, the agricultural land covers classified are mango, coconut, rice, corn, fallow, oil palm, banana and fallow. On the other hand, other non-agricultural land cover features were also classified such as water, road, grassland, shrub land, sand/bare rock/clay, buildings and non-agricultural trees.

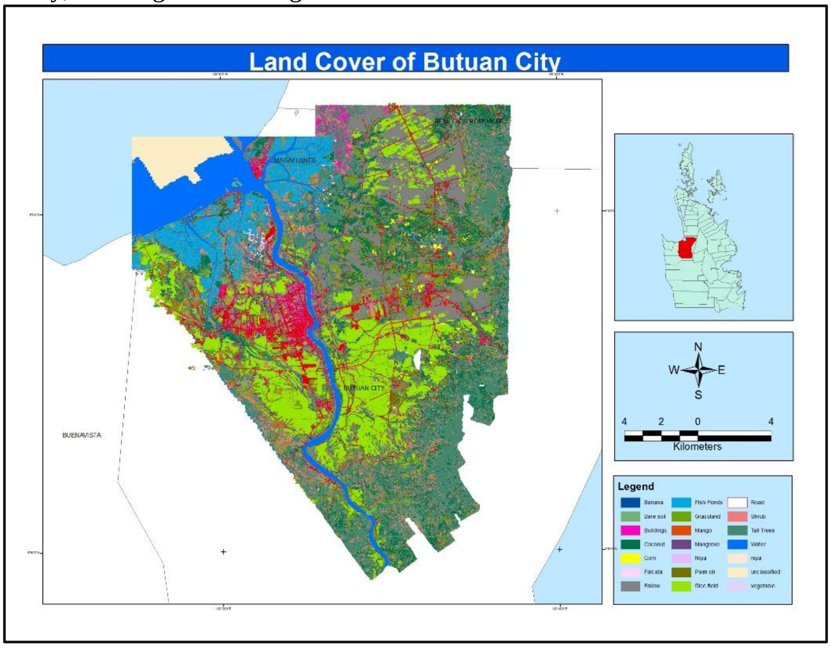


Figure 2. The Land Cover of Butuan City

Moreover, accuracy on the classification of resources (Figure 2) was assessed. Result shows that the developed optimized algorithm gives best acceptable result in extracting detailed agricultural resources by employing Object-Based Image Analysis (OBIA) classification. The accuracy of the classified detailed resource map with LiDAR data gained with high overall accuracy of 94.36% with Kappa Index Agreement (KIA) nearest to 93% as shown in Figure 3. The resulting accuracy shows high acceptable results for detailed classification mapping using LiDAR data coupled with orthophoto.

Error Matrix based on Samples

User Class \ S...	Shrub	Grassland	Rice field	Fallow	Road	Shadow	Buildings	Coconut	Tall Trees	Corn	Sum
Confusion M...											
Shrub	65	0	0	1	0	2	0	1	6	17	92
Grassland	2	117	1	0	0	0	0	0	0	0	120
Rice field	0	6	44	1	0	1	0	0	3	0	55
Fallow	0	3	0	609	2	1	7	0	0	0	622
Road	0	0	0	0	95	0	4	0	0	0	99
Shadow	1	0	0	0	0	97	1	1	1	0	101
Buildings	0	0	0	0	0	1	229	0	3	0	233
Coconut	0	0	0	0	0	0	0	126	7	0	133
Tall Trees	0	0	0	1	0	3	15	12	626	2	659
Corn	0	0	0	0	0	0	0	0	2	34	36
unclassified	0	1	0	1	0	1	5	0	6	0	14
Sum	68	127	45	613	97	106	261	140	654	53	
Accuracy											
Producer	0.9558824	0.9212598	0.9777778	0.9934747	0.9793814	0.915	0.8773946	0.9	0.9571865	0.6415094	
User	0.7065217	0.975	0.8	0.979	0.9595960	0.9603960	0.9828326	0.9473684	0.95	0.9444444	
Hellden	0.8125000	0.9473684	0.88	0.9862348	0.9693878	0.9371981	0.9271255	0.923	0.9535415	0.764	
Short	0.6842105	0.9	0.7857143	0.9728435	0.9405941	0.8818182	0.8641509	0.8571429	0.9112082	0.6181818	
KIA Per Class	0.954	0.9166371	0.9771983	0.9908426	0.9783930	0.911	0.8626007	0.8934515	0.9384397	0.6354447	
Totals											
Overall Accuracy	0.9436229										
KIA	0.9295039										

reduce expand Close

Figure 3. Accuracy Assessment of the Classified Detailed Agricultural Resource Map

3.2 Coconut and Mango Features Extraction

From the classified resources, coconut and mango features were extracted using eCognition software and converted to shapefile for GIS application. Tree height and crown area were among of the parameters extracted which were used in the estimation of the potential above ground biomass. Figure 4 and Figure 5 show the distribution of the coconut and mango crops in the city and its attributes. Result shows that there were a total of 164,725 segmented objects of coconut and 24,148 objects of mango.

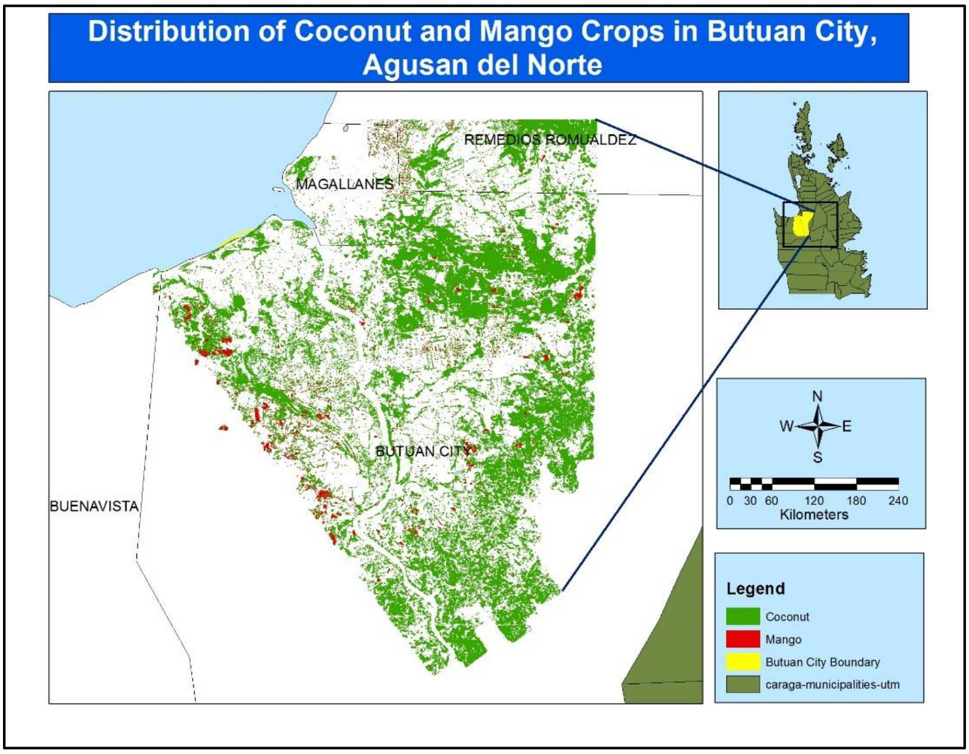
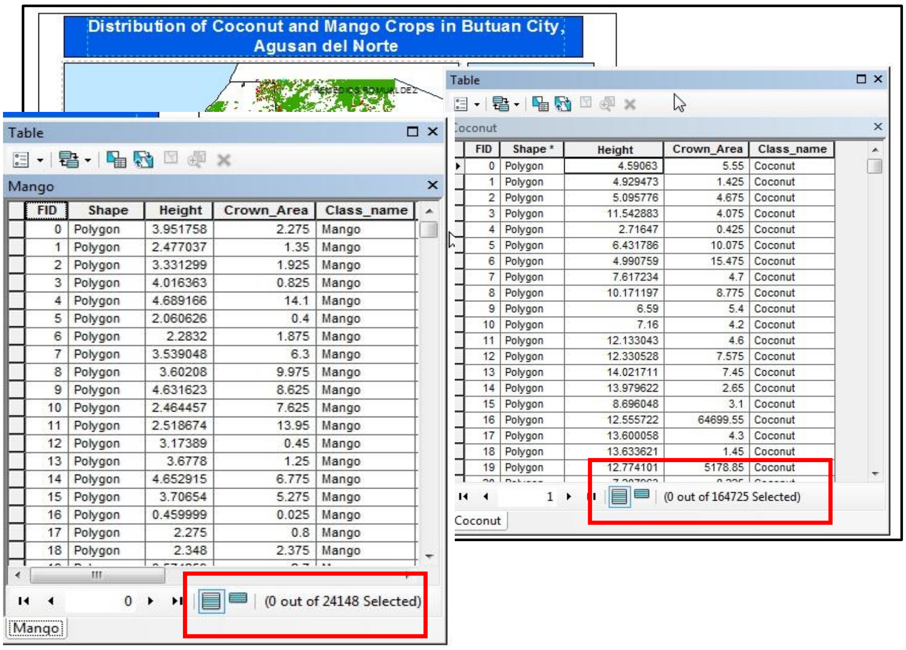


Figure 4. Extracted Coconut and Mango Features in Butuan City



FID	Shape	Height	Crown_Area	Class_name
0	Polygon	3.951758	2.275	Mango
1	Polygon	2.477037	1.35	Mango
2	Polygon	3.331299	1.925	Mango
3	Polygon	4.016363	0.825	Mango
4	Polygon	4.689166	14.1	Mango
5	Polygon	2.060626	0.4	Mango
6	Polygon	2.2832	1.875	Mango
7	Polygon	3.539048	6.3	Mango
8	Polygon	3.60208	9.975	Mango
9	Polygon	4.631623	8.625	Mango
10	Polygon	2.464457	7.625	Mango
11	Polygon	2.518674	13.95	Mango
12	Polygon	3.17389	0.45	Mango
13	Polygon	3.6778	1.25	Mango
14	Polygon	4.652915	6.775	Mango
15	Polygon	3.70654	5.275	Mango
16	Polygon	0.459999	0.025	Mango
17	Polygon	2.275	0.8	Mango
18	Polygon	2.348	2.375	Mango

(0 out of 24148 Selected)

FID	Shape *	Height	Crown_Area	Class_name
0	Polygon	4.59063	5.55	Coconut
1	Polygon	4.929473	1.425	Coconut
2	Polygon	5.095776	4.675	Coconut
3	Polygon	11.542883	4.075	Coconut
4	Polygon	2.71647	0.425	Coconut
5	Polygon	6.431786	10.075	Coconut
6	Polygon	4.990759	15.475	Coconut
7	Polygon	7.617234	4.7	Coconut
8	Polygon	10.171197	8.775	Coconut
9	Polygon	6.59	5.4	Coconut
10	Polygon	7.16	4.2	Coconut
11	Polygon	12.133043	4.6	Coconut
12	Polygon	12.330528	7.575	Coconut
13	Polygon	14.021711	7.45	Coconut
14	Polygon	13.979622	2.65	Coconut
15	Polygon	8.696048	3.1	Coconut
16	Polygon	12.555722	64699.55	Coconut
17	Polygon	13.600058	4.3	Coconut
18	Polygon	13.633621	1.45	Coconut
19	Polygon	12.774101	5178.85	Coconut

(0 out of 164725 Selected)

Figure 5. The Attribute Tables of Coconut and Mango Crops Distribution in Butuan City

Also, the height and crown area minimum, maximum, sum and the mean value of the coconut and mango were determined using GIS. It shows that the average height of coconut and mango tree in Butuan City were 7.64 m and 3.92 m, respectively as shown in Figure 2.

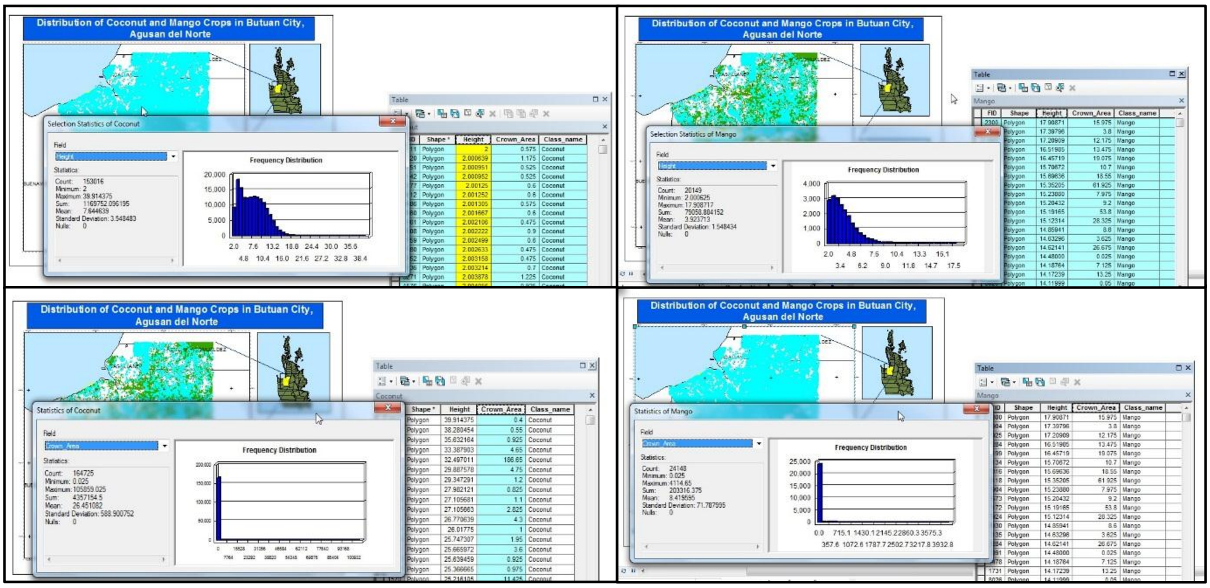


Figure 6. Statistics Data of Tree Heights and Crown Area of the Extracted Coconut and Mango Features

3.3 Tree Height, DBH Field Measurement and Statistical Analysis

To develop an allometric model of DBH estimation, tree height and diameter at breast height (DBH) of coconut and mango samples were measured and collected on site. Identification of sampling site was based on the area distribution of the extracted coconut and mango crops in the city using stratified sampling method. There were five (5) sampling sites of each crop visited of which a total of 100 samples were measured of each crop. The collected data was then analyzed using regression analysis to determine the relationship of the tree height to DBH. Based on the results shown in Figure 7, there were a positive relationship between DBH and the tree height of both crops at 95% level of confidence which simply means that the height also increase in every increase of DBH.

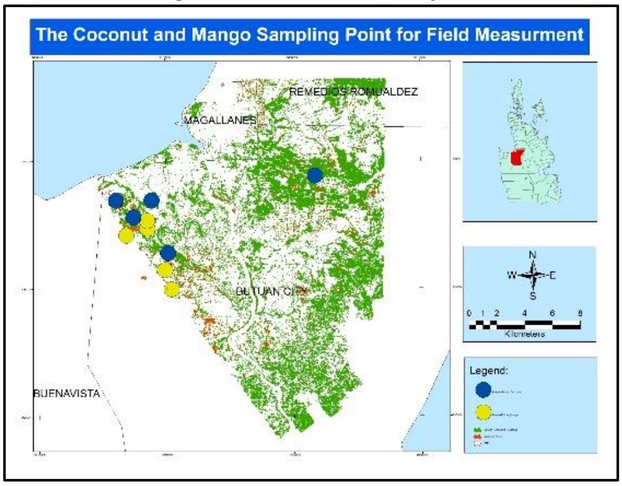


Figure 7. The Sampling Points of the Project

3.4 Development of Allometric Model

With the samples of data collected and subjected to Regression Analysis, the allometric model for estimation of DBH was developed. This model was used to estimate the diameter at breast height of coconut and mango tree of the known tree height in the extracted features from LiDAR derivatives. Figure 8 illustrates the relationship of the tree height to the diameter at breast height of coconut and mango trees. The highlighted red box was the allometric equation developed to estimate the DBH with corresponding R^2 value. The model shows that the increase in tree height give a little difference in the DBH since the slope of the line is less than 1. However, a little increase of the DBH gives significant increase of the tree height. Thus, the two variables are directly related to each other.

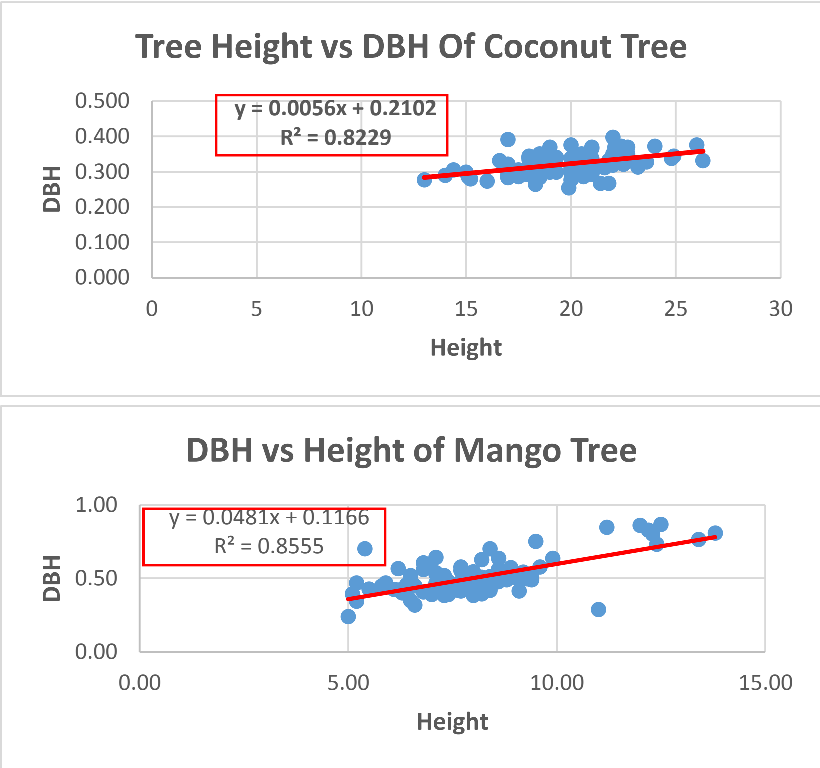


Figure 8. The Tree Height and DBH Relationship of Coconut and Mango Tree

3.5 Potential AGB Estimation and Map Generation

Using the developed allometric model and extracted features in the attribute tables, the estimated DBH was computed using GIS. This parameter was used to estimate the potential above ground biomass (AGB) of coconut and mango tree in Butuan City. Using the Brown (1997) biomass equation for tropical trees suited for areas with rainfall greater than 4000 mm/year in the lowlands, the distribution of potential AGB for coconut and mango trees in the city was determined and illustrated in Figure 9.

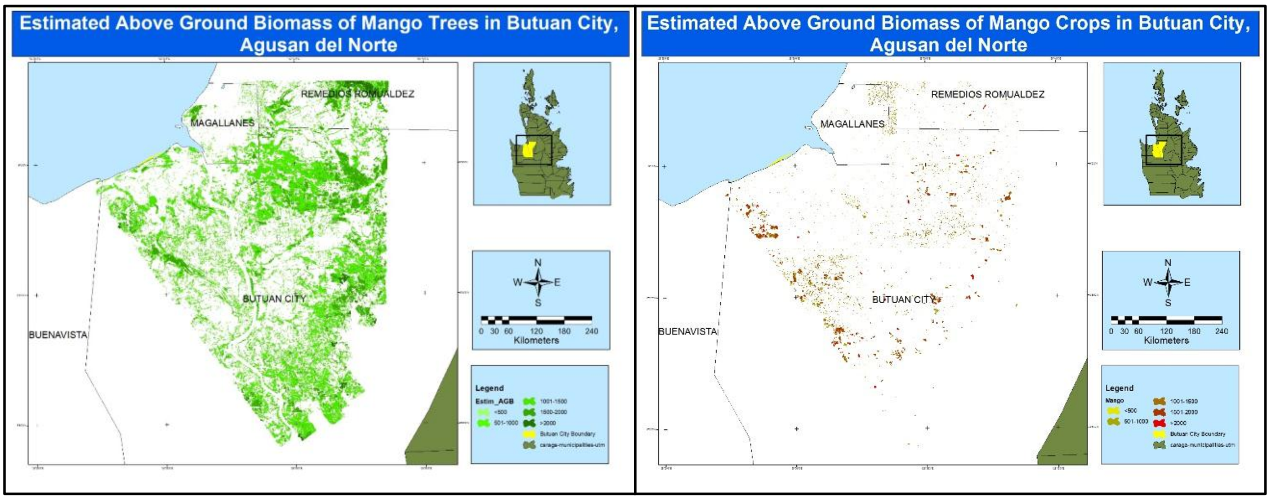


Figure 9.The Potential AGB Distribution of Coconut and Mango Trees in Butuan City, Agusan del Norte, Philippines

4. CONCLUSION AND RECOMMENDATION

The project demonstrated a remote sensing application in the estimation of the potential above ground biomass of coconut and mango trees in Butuan City. Object-based classification of high-value crops using an optimized SVM model using LiDAR data and Orthophoto was used to classify the different resources in city. The developed optimized method applied in the classification gained with a very high overall accuracy resulted to a significant above ground biomass estimation. The researchers concluded that the practical application of LiDAR data (Normalized Digital Surface Mod [nDSM] is greatly enough to produce AGB estimation. Hence, the output of this project will be essential in several uses such as monitoring and assessment of the physiological structural for crop management practices, yield and carbon stock estimation. However, the researchers recommended more number of sampling areas, samples and other variables for AGB estimation may be consider to assess more the accuracy of the model.

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