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Utilization of LiDAR Data for Agricultural Land Cover Map and Potential Biomass Renewable Energy of Anao Tarlac Using Object Based Image Analysis

R. T. Alberto[1], G. B. Damian[2], E. E. Camaso[3], M. F. Isip[4]

[1]College of Agriculture, Central Luzon State University, Muñoz, Nueva Ecija

[2,3,4]Phil-LiDAR 2 Project, Institute for Climate change and Environmental Management (Phil-LiDAR 2, ICCEM), Central Luzon State University, Muñoz, Nueva Ecija

([1]travert2157@gmail.com, [2]virysses10@gmail.com, [3]elie.camaso7@gmail.com, [4]miguelito_isip21@yahoo.com)

Abstract- Light Detection and Ranging (LiDAR) is a remote sensing method that uses light in the form of a pulsed laser to measure ranges to the Earth. LiDAR produces mass point cloud datasets that can be managed, visualized, analyzed, and shared using ArcGIS. Using Object Based Image Analysis (OBIA), the LiDAR point cloud was investigated to produce agricultural land cover map and estimate the biomass potential for renewable energy of Anao, Tarlac. Different software were used to generate lidar point cloud attributes such as intensity, number of return, Digital Terrain Model (DTM), Digital Surface Model (DSM), Elevation, Curvature, Red Blue Green (RBG), Hue Saturation and Value (HSV) and Green Red Vegetation Index (GRVI). The lidar point cloud attributes were loaded to E-Cognition software for Object Based Image Analysis to produced high resolution agricultural land cover map, the classified and delineated production area of Rice, Corn and Sugarcane were used as basis in computing the potential biomass energy.

The produced agricultural land cover map from LiDAR using Object Based Image Analysis was effectively tested in the Municipality of Anao, Tarlac with overall accuracy and kappa coefficient of 94.5% and 0.92, respectively. The result showed that out of 2,661.26 hectares total land area of the Municipality, 986.25 hectares are devoted to Corn, 283.75 hectares and 10.85 hectares are devoted for Rice and Sugarcane production, 920.86 hectares are fallow which intended for rice production during rainy season and 176.51 hectares are Mango plantation the remaining 283.75 hectares are built up, water, road, grassland and non-agricultural trees. The estimated biomass potential energy for corn and rice are 4.57 million kwh and 1.89 million kwh.

Keywords- *LiDAR, OBIA, LiDAR Point Cloud, Lidar Point Attributes*

I. INTRODUCTION

Land cover refers to the physical characteristics of earth's surface, captured in the distribution of vegetation, water, soil and other physical features of the land, including those created solely by human activities e.g., settlements (Rawat, 2015). With the use of remote sensing and Geographical Information System (GIS) techniques, land cover mapping has given a useful and detailed way to improve the selection of areas designed to agricultural, urban and/or industrial areas of a region (Selcuk et al., 2003). With the help of remote sensing technologies, the exact location and known agricultural areas of different crops are creating ways to the possibility of determining the potential biomass energy sources. Biomass such as rice hulls, Rice straw, Bagasse, corn cobs, coconut husk and others alike has been recognized as an alternative source of energy because of its availability and abundance (Orge et.al, 2017).

Different satellite imageries are available on the web that can be harnessed to generate land cover maps such as Landsat, Sentinel2-3, USGS earth explorer, LiDAR data and others alike. LiDAR or Light Detection and Ranging is a remote sensing technology that collects 3-dimensional point clouds of the Earth's surface. This technology is being used for a wide range of applications including high-resolution topographic mapping and 3-dimensional surface modeling as well as infrastructure and biomass studies (USGS, 2015).

LiDAR data can be used to produce detailed high resolution agricultural land cover map as well as the estimation of potential biomass renewable energy resources. The extraction of point clouds of LiDAR data to produce high resolution agricultural land cover map will undergone different algorithm such as Object Bases Image Analysis using Support Vector Machine (SVM) allows the incorporation of different properties such as spectral, geometric and textural properties for image classification (Phil-LiDAR 2, 2014). Thus, this application can be used to generate agricultural land cover features especially the crops for specific purposes.

II. OBJECTIVES

The general objective of the study was to produce detailed agricultural land cover map of the Municipality of Anao, Tarlac. Specifically it aims to:

1. Determined the total land area (ha) devoted to different crops such as Rice, Corn and Sugarcane, and
2. Assessed the potential biomass renewable energy of Rice, Corn and Sugarcane.

III. MATERIALS AND METHODS

A. Datasets

The LiDAR datasets used in the study were flight lines/flight strips from PHIL-LIDAR 1 project or Hazard Mapping of the Philippines using LiDAR. The LiDAR flights are AGNO_6C to AGNO 6F acquired from April 17 to April 22, 2013, the name of the flights were name after Agno River Basin.

B. Location of the study

The Municipality of Anao, Tarlac was the study site for mapping of detailed agricultural land cover and determination of potential biomass renewable energy sources (Figure 1). The study site is the smallest municipality of Tarlac in terms of total land area of 2,661.26 hectares. The Municipality is located at 15°43′44″ North latitude and 120°37′34″ East longitude (Wikipedia, 2016). The municipality is composed mainly by agricultural production such as rice, corn and sugarcane production.

C. Methodologies and Conceptual Framework

1) LiDAR and Orthophoto image processing

The LiDAR data and Orthophoto were processed using different software to generate different point cloud derivatives to extract agricultural land cover map. The software's used in the study were BLAST2DEM which is used to produce Digital Terrain Model (DTM) and Digital Surface Model (DSM), LASgrid used to generate building layer, Intensity and Number of returns, while Envi was used to produce the Red, Green Blue (RGB) Layers, Green Red Vegetation Index (GRVI), Hue Saturation and Value (HSV), the ArcGIS on the other hand was used to produced normalized DSM (nDSM), Curvature, Road layer, Water Layer, training points and validation points (Alberto et.al, 2016). Table 1 shows the different derivatives used in the study to produced agricultural land cover map (Phil-LiDAR 2, 2014).

Figure 2 shows the different point cloud attributes used to extract the detailed agricultural land cover map of Anao, Tarlac City, the total area of sample derivatives is 794.00 hectares.

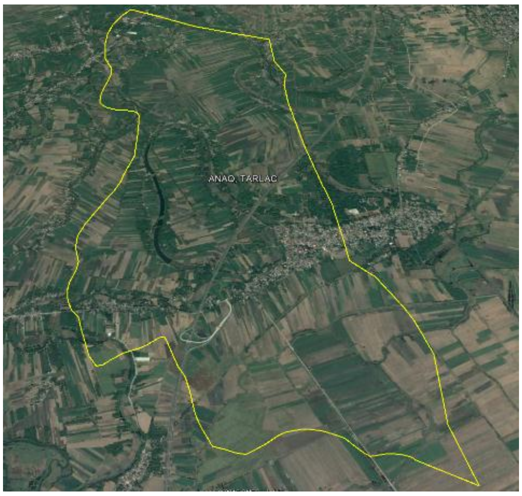

Figure 1. The study site, Anao, Tarlac (Google earth, 2017)

TABLE I. LIST OF POINT CLOUD ATTRIBUTES

Data Sources	Derivatives	Description
LiDAR	Intensity	Created from the whole intensity spectrum of LiDAR point cloud. Generally, objects with high reflectivity have higher intensity return than dark features
LiDAR	Number of Returns	Created from number of return of LiDAR point clouds. Useful in separating buildings and trees, thus, trees have higher number of returns than buildings
LiDAR	nDSM	DTM subtracted from DSM to obtain the height of the objects above the ground. Useful in separating tall and short vegetation and highlight the elevated and low lying features
LiDAR	Curvature	Second derivative of a surface or slope of the slope
Orthophoto	RGB	Original bands of the Orthophoto, show spectral properties of features
Orthophoto	HSV	Transformation applied to the original Orthophoto image in the HSV color space. Intensity Image is substituted to the value portion upon transformation back to RGB color space
Orthophoto	GRVI	Index to highlight the green portion of the image. Useful for identifying vegetation and non-vegetation features. Calculated based on the red and green bands of the Orthophoto image.

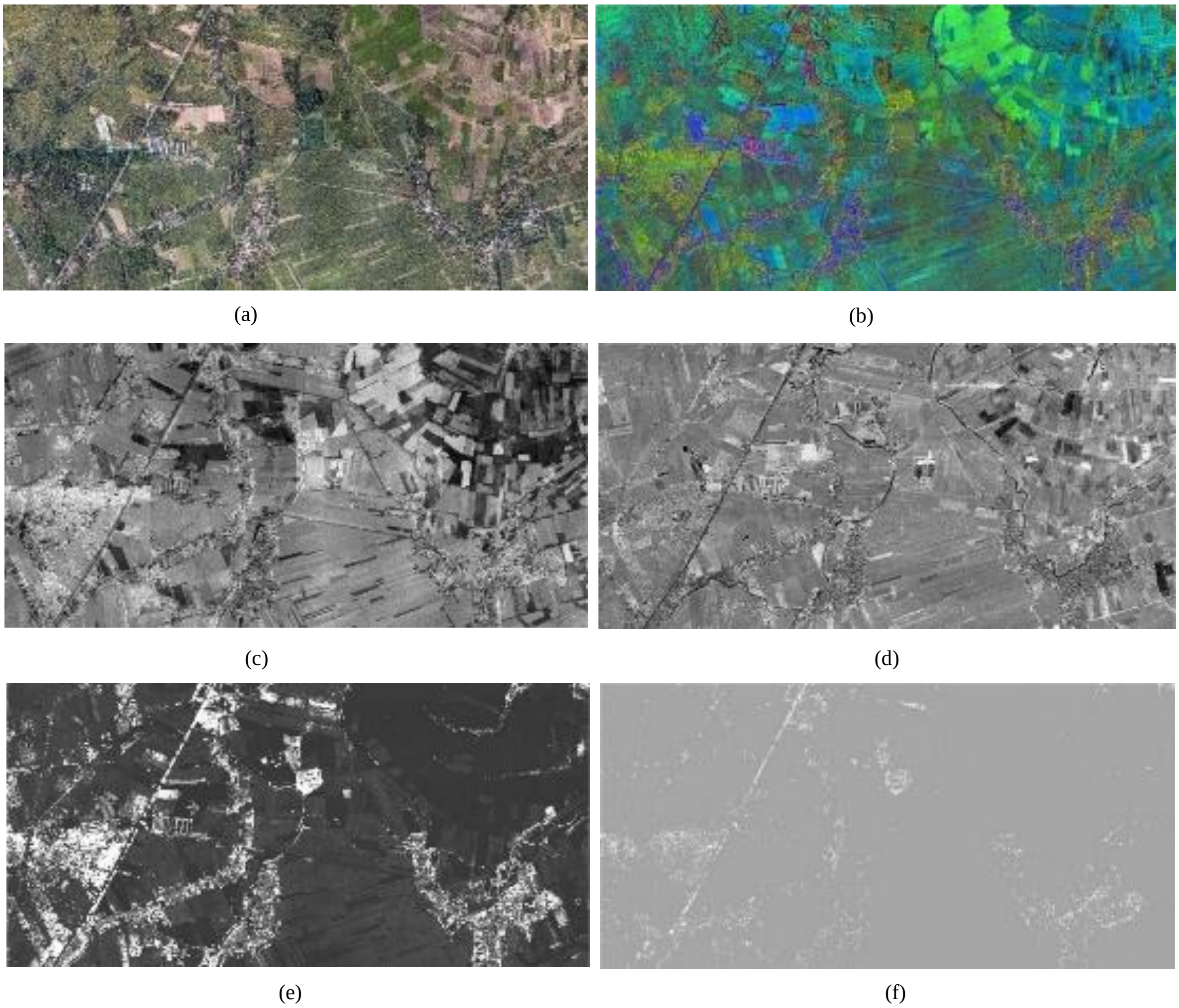

Figure 2. The different point cloud attributes/Derivatives used in the study

2) Object Based Image Analysis

The generated derivatives were loaded to eCognition developer for object based image analysis. The derivatives were segmented into chessboard segmentation to properly separated the Built Up, water and Road classes, multi-threshold segmentation to separate the tall features such as Trees and Mango and multiresolution segmentation to segment the short features such as Agricultural crops, Grassland and Fallow/bareland. After segmentation, Support Vector Machine was apply with the training points to properly classify the different features present in the Municipality. The support vector machine is a supervised learning method that generates input-output mapping functions from a set of labeled training data (Wang, 2005). The produced different classes were undergone accuracy assessment to determine the validity of the classification. If the accuracy is greater than 90%, the different features were exported into shapefiles for GIS post processing.

3) Field Validation and Accuracy assessment

Field validation was done to obtain the ground truth of the different classes, the validation points were strategically scattered to the different classes (Figure 3). Field validation is an important step in the processing of remote sensing data, it determines the information value of the resulting data to a user (Haroun et.al, 2013). The field validation data was used to determine the accuracy assessment of the generated agricultural land cover map.

4) GIS post processing

GIS Post processing involves the Minimum Mapping Unit (MMU) or elimination of smallest entity size that can be seen in the map. This can be done by copying the level of the final classification and removing objects located within *No Data* areas. Area of polygons will be calculated using spatial analysis, this can be performed by exporting original and merged objects from the final classification level. The areas calculated will be arranged in ascending order to recognize the areas to be eliminated. The final smoothed shapefiles will converted into geodatabase and undergone schema to produce the detailed agricultural land cover map (Phil LiDAR 2, 2016).

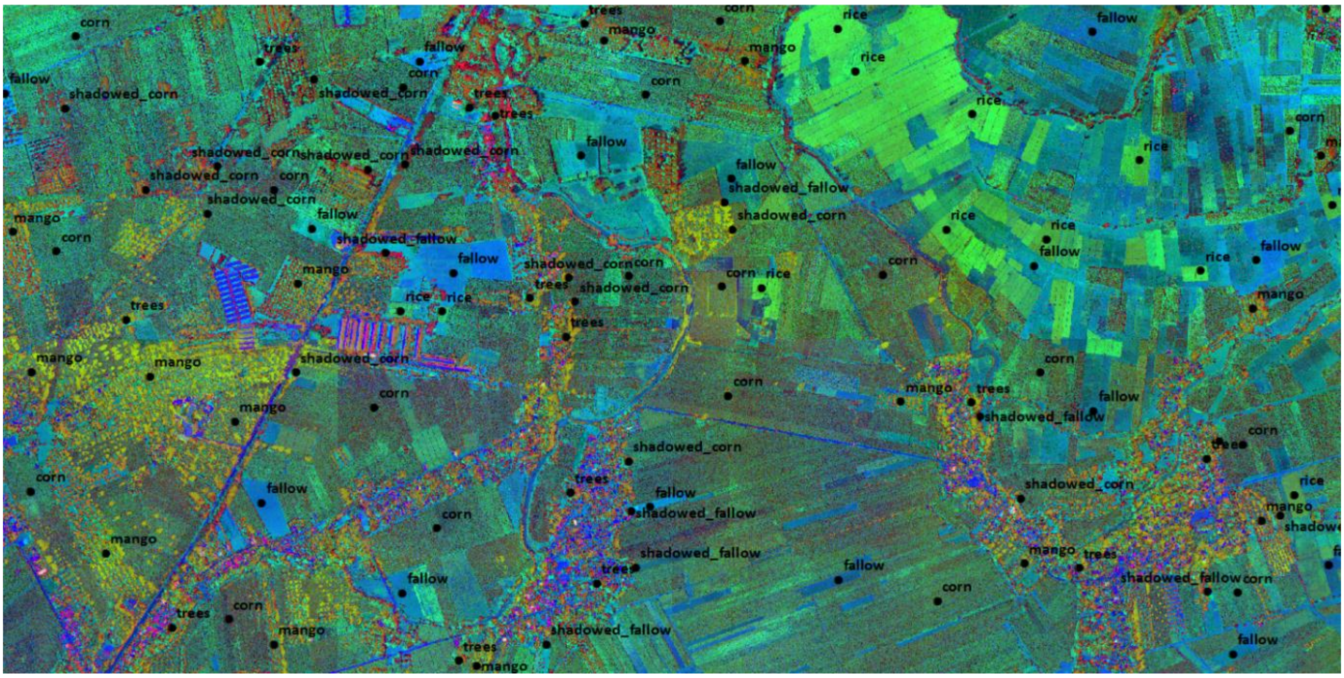

Figure 3. The Field validation points of the study

5) Biomass Energy computation

Using the generated agricultural land cover map of Anao, Tarlac, and the total area of rice, corn and sugarcane was calculated by means of spatial analysis. According Voivontas, et al (2001) as cited by Alberto et.al (2017) the biomass theoretical potential (B_n) is the total production of residues in a region (equation 1), and the available biomass potential (B_{av}) is the energy content of B_n (equation 2)

$$B_n = \sum_n A_n Y_n \tag{1}$$

Where:

A_n = cultivated area for crop *n* (ha)

B_n = biomass theoretical potential for crop *n* (Mg /year)

Yn = residue yield for crop *n* (Mg/km^2/year)

$$B_{av} = \frac{f_g \sum_n B_n a_n LHV_n}{A_r} \tag{2}$$

Where:

a_n = biomass available for energy production from crop *n* (%)

A_r = area of the region under consideration (km^2)

B_n = biomass theoretical potential for crop *n* (Mg of residue/year)

B_{av} = biomass available potential (MJ/km^2/year)

F_g = efficiency of the biomass collection procedure (%)

LHV_n = lower heating value of the residue from crop *n* (MJ/kg)

6) Conceptual framework

The methodology in this study includes three processes: the Pre-processing, Data Processing and Post-Processing. In Pre-Processing, the LiDAR data and Orthophoto images were utilized to generate different derivatives to use in data processing. In data processing, all derivatives were loaded in Ecognition developer for Object Based Image Analysis using Support Vector Machine (SVM). Lastly, in post processing, the computed areas of agricultural crops together with the BAS data, the biomass potential was computed. Figure 4 shows the conceptual framework of the study (Alberto, 2016).

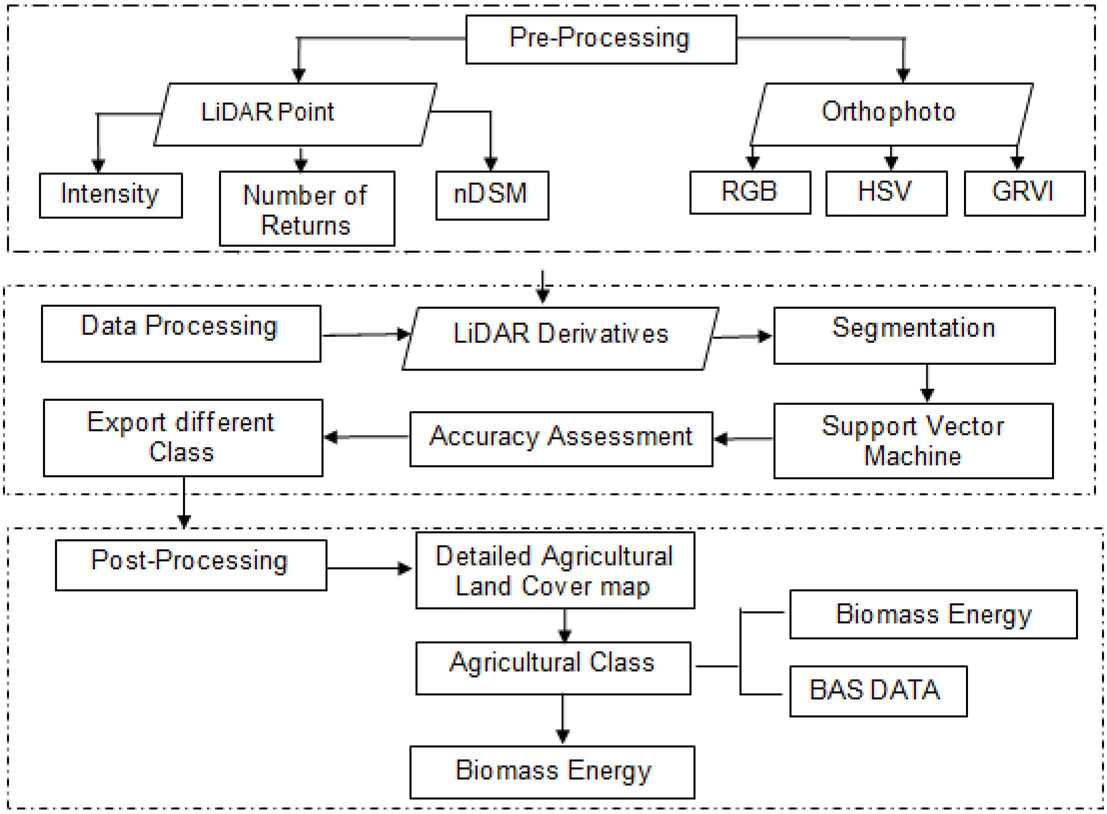

Figure 4. The conceptual framework of the study

IV. RESULTS AND DISCUSSION

A. Detailed Agricultural Land Cover Map of Anao, Tarlac

The Agricultural land cover map of Anao, Tarlac was completed using available LiDAR data and existing algorithms. Using Support Vector Machine (SVM) the LiDAR data of Anao, Tarlac was successfully extracted the different features of the Municipality. Figure 5 shows the generated agricultural land cover map of Anao, Tarlac. The Municipality has 10 land cover consists of rice, corn, sugarcane, fallow/bareland/ mango, building, water, road and trees.

Results shows that the largest portion of the municipalities is covered by Corn with a total area of 986.21 ha followed by fallow/bareland and rice with a total area of 920.86 ha and 283.04 ha, respectively (Table 2). It was learned during the field validation that the fallow area was planted by rice, corn and sugarcane. Also, the municipalities has mango plantation and non-agricultural tress with an area of 176.55 ha and 175.92 ha, respectively. The Sugarcane is the least cover with an area of 10.85 ha. The Average accuracy and *kappa* coefficient of the produced detailed agricultural land cover map of Anao, Tarlac were 94.5% and 0.92, respectively.

TABLE II. DISTRIBUTION OF DIFFERENT LAND COVER OF ANAO, TARLAC

Classes	Area (ha)
Building	44.61
Corn	986.21
Fallow/Bareland	920.86
Grassland	15.25
Mango	176.55
Non Agricultural Trees	175.92
Rice	283.04
Road	20.62
Sugarcane	10.85
Water	27.35
Total	2,661.26

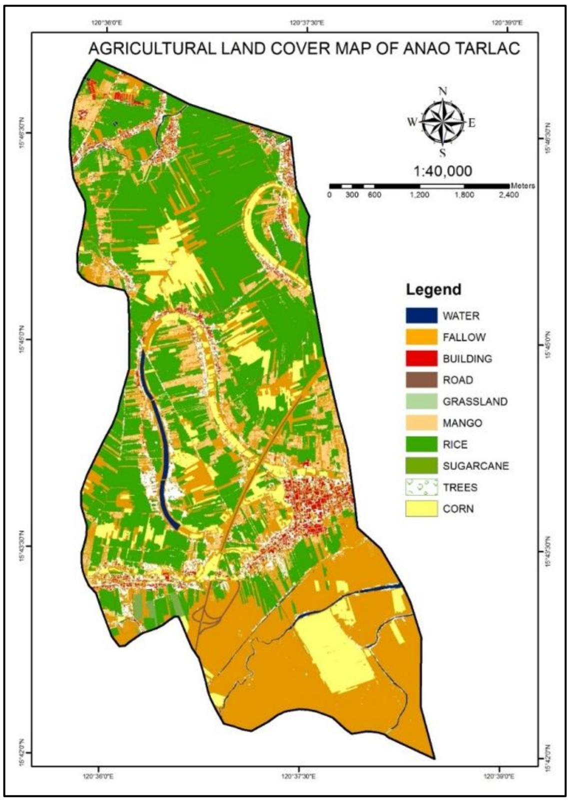

Figure 5. The agricultural land cover map of Anao, Tarlac

B. BIOMASS POTENTIAL ENERGY

Table 3 shows the average crop yield of Tarlac (BAS, 2015), and table 4 shows the available energy of different agricultural biomass, the data is needed in the computation of potential biomass renewable energy. The residue conversion factor of corn and rice were 1.8306 metric ton per ha and 1.1475 metric ton per hectare, respectively, (REMap, 2016). Using the generated agricultural land cover map, the area planted with corn, rice and sugarcane are 986.21 ha, 283.04 ha and 10.85 ha, respectively. With the computed area and 73.69 % availability of corn cobs, the B_n and B_{av} of the corn cobs in the municipality was obtained through Equations (1) and (2) which are 1,805.42 Mg and 4.57 million kwh, respectively. The latter value will be the amount of energy that the corn cob can provide per year, since corn is planted annually. The rice hull potential of the municipality is 1.89 million kwh for one cropping and has a total of 3.78 kwh per year. There is no available biomass potential for bagasse, the sugarcane of the municipality is dedicated for sugar production.

TABLE III. THE AVERAGE CROP YIELD OF RICE, CORN AND SUGARCANE OF TARLAC

Province	Rice		Corn		Sugarcane	
	MT/Ha	Source/Year	MT/Ha	Source/Year	MT/Ha	Source/Year
Tarlac	4.25	BAS/2015	6.78	BAS/2015	55.86	BAS/2014

TABLE IV. THE AVAILABLE AGRICULTURAL BIOMASS FOR ENERGY PRODUCTION

Agricultural Biomass	Available for Energy Production, %	Efficiency of Collection, %
Corn cobs	73.69	98.29
Rice Hulls	35.35	84.61
Bagasse	0.00	100.00

V. SUMMARY AND CONCLUSION

LiDAR data with the use of Object Based Image Analysis was successfully tested to generate agricultural land cover map of Anao, Tarlac. The results showed that the average accuracy and *kappa* coefficient of the generated agricultural Land Cover map were 94.5% and 0.92, respectively. In this study, the combination of simple spatial analysis and Object Based Image Analysis is suited in determining the potential biomass renewable energy of the Municipality.

VI. RECOMMENDATION

Refining the segmentation and applying manual classification to the miss classified features will improved the accuracy of the generated map. Also, improving the training points will result to better features classification and avoid manual classification. It was also recommended to use the LiDAR data in different precision agriculture application.

VII. ACKNOWLEDGEMENT

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