RESOURCE MAPPING OF HIGH VALUE CROPS IN CAVITE AND DEVELOPMENT OF THE ALGORITHM FOR DETECTING COCONUT, SUGARCANE, AND RICE USING LIDAR DATA

Alejandro Ballado Jr.[1,2]; Ramon Garcia[1,2]; Lei Anne C. Barrientos[1]; Lorraine Mae U. Catenza[1]; Rhoniel Guillen E. Redula[1]; Zylene Anne C. Timajo[1]; Glenn V. Magwili[1,2]; Jennifer Dela Cruz[1,2]; Sarah Alma P. Bentir[2]; Shydel M. Sarte[2];
[1]School of EECE, Mapúa University, Muralla St. Intramuros 1002 Manila, Philippines
[2]School of Graduate Studies, Mapúa University
ahballado@mapua.edu.ph, rggarcia@mapua.edu.ph, lacbarrientos@mymail.mapua.edu.ph, lmucatenza@mymail.mapua.edu.ph, rgeredula@mymail.mapua.edu.ph, zactimajo@mymail.mapua.edu.ph, gvmagwili@mapua.edu.ph, jcdelacruz@mapua.edu.ph, sapbentir@gmail.com, shydelsarte@gmail.com

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ABSTRACT: included as the most high value crops in the world. The demand for the production of crops is also rising given that food is one of the basic human necessities. The Philippines has a vast number of agricultural resources. However, monitoring is one of the problems in agricultural industry. Due to the fast paced economy and rapid land use and land cover changes; it is mostly important to produce detailed resources maps. This study investigated the prospective of LiDAR data that provides explicit information in delineating land use and land cover. Nevertheless, considering the labor and cost of providing the whole area with LiDAR data might be very challenging; hence, this study developed methodologies to generate maps using LiDAR data and satellite imagery. The optimization of the classification has been applied in image analysis with both qualitative and quantitative measures using Support Vector Machine. The utilization of the features has been described in this study. Furthermore, the study presented the performance of pixel-based and object-based classification. The experiments conducted in six different areas in the province of Cavite. Results show that pixel based algorithm provide higher result than object based given that the classes are in spatially large. Nevertheless, object-based classification provided detailed information with implicit information of the classes in the area.

1. INTRODUCTION

The agricultural growth of the Philippines would continue to drastically increase by the year 2020, thus increasing the per capita consumption of high-valued crops, according to the Philippine Institute for Development Studies. In unison with the country’s growing population, the demand for the production of crops is also rising given that food is one of the basic human necessities. The Department of Agriculture is the one responsible in yield production in the Philippines. Some provinces in the country are where several high value crops are cultivated. These crops refer to non-traditional crops, e.g. vegetables, fruits, condiments, and spices. These are high in value and can be exported. Problems encountered in locating crops are due to outdated resource map. Mapping of the high value crops in the Philippines is not yet available due to lack of resource and information about crop vegetation.

The main objective of this study is to create a resource map of agricultural resources in the entire Cavite province, Philippines using LiDAR data and Landsat imagery by developing an algorithm to determine the location of different high value crops, namely Coconut, sugarcane, rice.

2. RELATED WORKS

Mapping of land cover and land use has been widely used with different application including forestry, natural hazards, and urban climatology, and agriculture (David L. , Sarte, Laguerta, & Ballado, 2016). One of the most popular methods in remote sensing is using the image analysis wherein multiple input layers were utilized during the image segmentation with both qualitative and quantitative measures that is used to select and evaluate the resulting image objects (Mui, He, & Weng, 2015). Recently, Object Based Image Analysis has been become popular in extracting features wherein the goal of the segmentation is to group neighboring pixels to create an explicit object (David L. G., Sarte, Pula, & Ballado, 2016).

The most successful image segmentation algorithm has been done is the multi-resolution segmentation (MRS) in the GEOBIA framework (Ma, Cheng, Li, & Ma, 2015). Multi-resolution segmentation is a bottom-up region merging technique wherein small segmented objects were merged into a larger region that is based on the similarity of the spectral and spatial features (homogeneity) of the adjacent cell (Ma, Cheng, Li, & Ma, 2015). MRS relatively complex and a user-dependent method wherein the scale, shape, and compactness are the main parameters that is needed to be manipulated set by the user (Ma, Cheng, Li, & Ma, 2015). However, due to increase of demand in mapping Land Use Land Cover (LULC), it might be more practical when use different data since satellite imagery have been become available to the public to aid production of cover maps (David L. G., Sarte, Pula, & Ballado, 2016).

The method used by (David & Ballado, 2017) used the LiDAR-derived and multispectral to extract LULC objects using Support Vector Machine (SVM) and has proven that height metrics can be very useful in classifying agricultural crops.

2.1. Support Vector Machine

SVMs are general learners based on Structural Risk Minimization principle taken from computational learning theory with the basic form based from linear threshold function and can also be learned polynomial classifiers using an appropriate kernel function (Zoonen, Toni, & van der Meer, 2016). The basic idea of SVM is plot the original input data space to a higher dimensional or infinite-dimensional feature space to differentiate different variables (Bhattacharya, Carr, & Pal, 2016). In SVM, support vectors (samples) are one of the most significant in SVM algorithm. Where the training data set $\{x_i, y_i\}_{i=1}^{n}$ with $x_i \in R^d$ are the input vectors and $y_i \in \{-1, +1\}$ are the class labels and used the function $\varphi(\cdot): R^d \rightarrow R_h^d$ (Bhattacharya, Carr, & Pal, 2016). The purpose of SVM is to search the hyperplane that can totally separate distinct variables (Insom, et al., 2015)

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3. METHODOLOGY

3.1. Study Area and Materials

LiDAR data points obtained in Cavite are provided by the Phil-LiDAR 2 Program, also known as the Nationwide Detailed Resources Assessment using LiDAR, is a three-year program funded by the Department of Science and Technology (Blanco, Tamondong, Perez, Ang, & Paringit, 2015). The data was acquired last February to May 2014. Lidar data points were collected during flight of the plane containing the laser scanner that scans the ground and these laser pulses will be recorded as points. The collection of these points is technically called point cloud. Lidar data can contain significantly more information may include the returns, the number of returns, the time, and the source of flight line.

3.2. Conceptual Framework

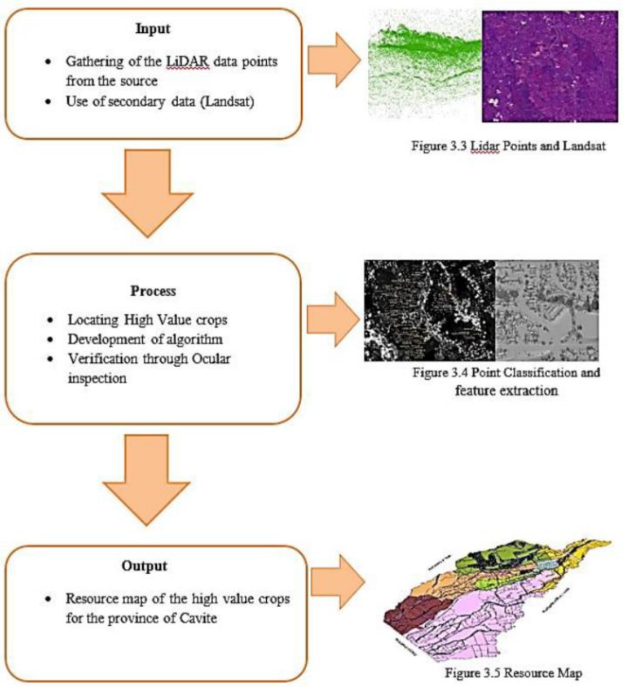

Figure 1. Conceptual Framework

This study is an innovation in terms of agricultural development. LIDAR data can be used to detect the slope, intensity, and elevation of the high value crops. Since the Philippines has a vast number of agricultural resources, the development of the agricultural resource map using LIDAR Technology can be a great help in using these resources wisely and help the Philippines grow agriculturally and economically. Also, crops and vegetation can be tracked down if land hectares decrease into a value.

3.3. Generating Resource Map Using Lidar Data

LiDAR data points obtained in Cavite are provided by the Phil-LiDAR 2 Program, also known as the Nationwide Detailed Resources Assessment using LiDAR, is a three-year program funded by the Department of Science and

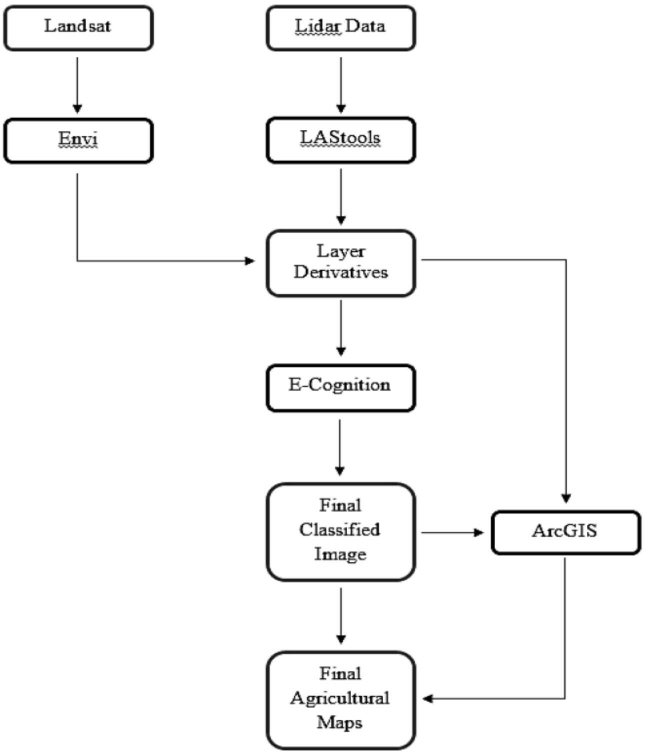

Figure 2. Utilization of Software Using LiDAR data

Figure 2 shows the processes and the software used in which the Lidar data undergone in order to generate the resource map. LasTools is used for pre-processing of the Lidar data and utilize the information inside each lidar point clouds. On the other hand, Envi software is used to utilize digital numbers that are available in Landsat 8 imagery. Each layer has distinctive feature that will set one crop above among other crops. Object based image analysis is applied in classifying objects based from the LiDAR produced data while pixel based has been used to generate classification using satellite imagery using Ecognition. Training and validation were performed using ArcGIS software

3.3.1. Preprocessing LiDAR data

The image layers were generated through LasTools. The information extracted are based from the following: Average Elevation, Average Intensity, Average Returns, DSM, DTM, Highest Elevation, Highest Intensity, Highest Returns, Hillshade, Lowest Elevation, Lowest Intensity, Lowest Returns, NDSM, PF CHM, and Slope.

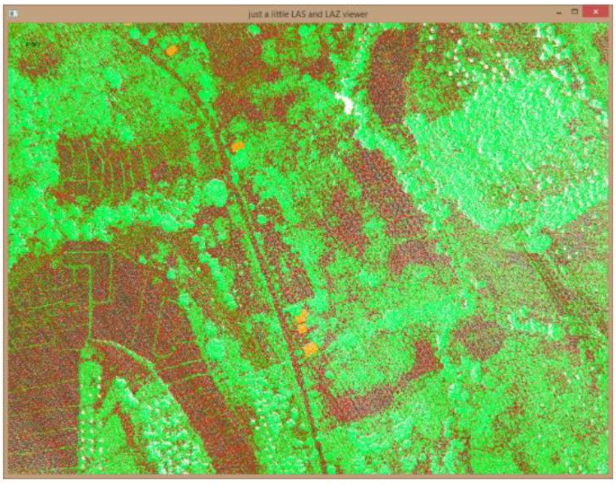

Figure 3. LiDAR point clouds view from LasTools

3.3.2. Sampling

Coconut, sugarcane, and rice are abundant crops in the study area. Input layers derived from LiDAR data such as Pit Free Canopy Height Model (Khosravipour, A., 2013), NDSM, and Highest Intensity, the three crops can be located through visual and can verify its height through use of layers. PF CHM and NDSM determine the height of the vegetation while Highest Intensity determines the amount of light returned or its intensity. The intensity can be used to determine rice and PF CHM or NDSM in determining coconut and sugarcane.

Using the Highest Intensity layer, rice has a value of less than 40. Intensity is the return strength of the laser pulse meaning it is the reflectivity of the object. Lighter shades of objects are relatively on ground meaning it captures high amount of light.

However, PF CHM captures the elevation of the object. Ground objects are the darker while no ground objects are lighter. Coconut’s height ranges from 9-20 meters while sugarcane’s height ranges from 2-3 meters. Sugarcane and coconut used PF CHM layer. NDSM can be a substitute if there is missing data on a PF CHM layer.

The training and validation points are created based from ground validation and visual interpretation using secondary datasets. Training points are the initial classes of the object then the accuracy of these points will be assessed through validation points. Coconut, sugarcane, rice, water, barren, other vegetation, and non-vegetation are able to generate map. Other vegetation includes other high value crops such as mango, banana, etc. This is the crucial process in creating the algorithm for the three crops because the classification will be dependent on the thematic layer made in Arcmap. Thematic layer is a set of merging points containing the class hierarchy. Sampling points used is based from simple random sampling.

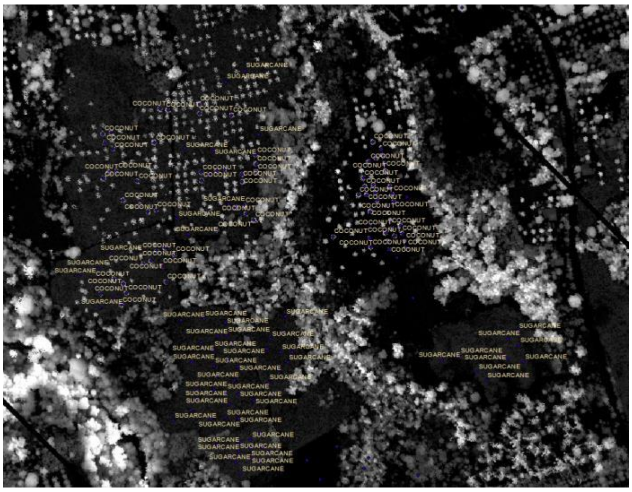

Figure 4. Sampling Points

3.3.3. Classification using Object Based Image Analysis

Classification has been done using Ecognition Software. Fig. 5 denotes the methodology

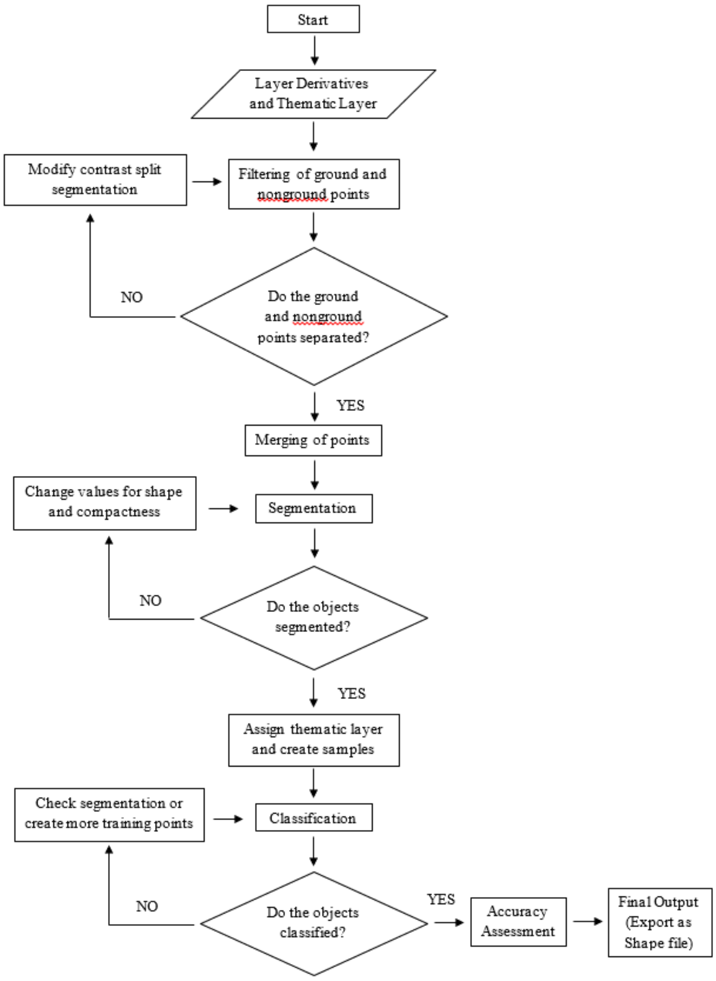

Figure 5. Development of Algorithm for Coconut

There is a need to filter ground and non-ground points because this will be the basis on determining what high value crops are planted on the ground (ground vegetation) and those that are not. There is a need for doing contrast split segmentation so there will be a split on bright objects and dark objects. The image layer is the layer used for the contrast split segmentation process and is very essential because each developed layer produce different bright dark objects. The class of bright objects is determined as non-ground points and the class of dark objects is determined as ground points.

Non-ground points are merged together for segmentation through the ‘merge region’ algorithm (Figure 5). Multiresolution segmentation (Figure 5) is done on the merged no ground points. The shape and compactness parameters depend on how big or small the segmentation is. Higher values result in bigger segmentation while lower values result to smaller segmentation. Values should be greater than 0.1 but less than 0.9.

The Support Vector Machine Algorithm (SVM) is a processing technique that classifies an object from sample points that possesses the same property. Values of each layer are averaged using Mean. The training points from the previous process plays an important role since samples that will be average will be derived here. After the averaging of values, samples will be distributed and will look for other objects with the same property. Those found objects with the same property now belong to a class.

Since there is possible misclassification upon doing the SVM classifier due to training points and segmentation, the ‘assign class’ algorithm is used to refine a certain class. Stated in the class filter is the class or classes that need to be screened and is converted into another class. A threshold condition is assigned in the class that needs to be refined. The values that will satisfy the given condition will be transformed into another class specified. A layer derivative most especially PF CHM is used for assigning conditions since it is suitable in determining the height of the coconut and sugarcane.

3.4. Extraction of Coconut, Sugarcane, and Rice Using Landsat Data

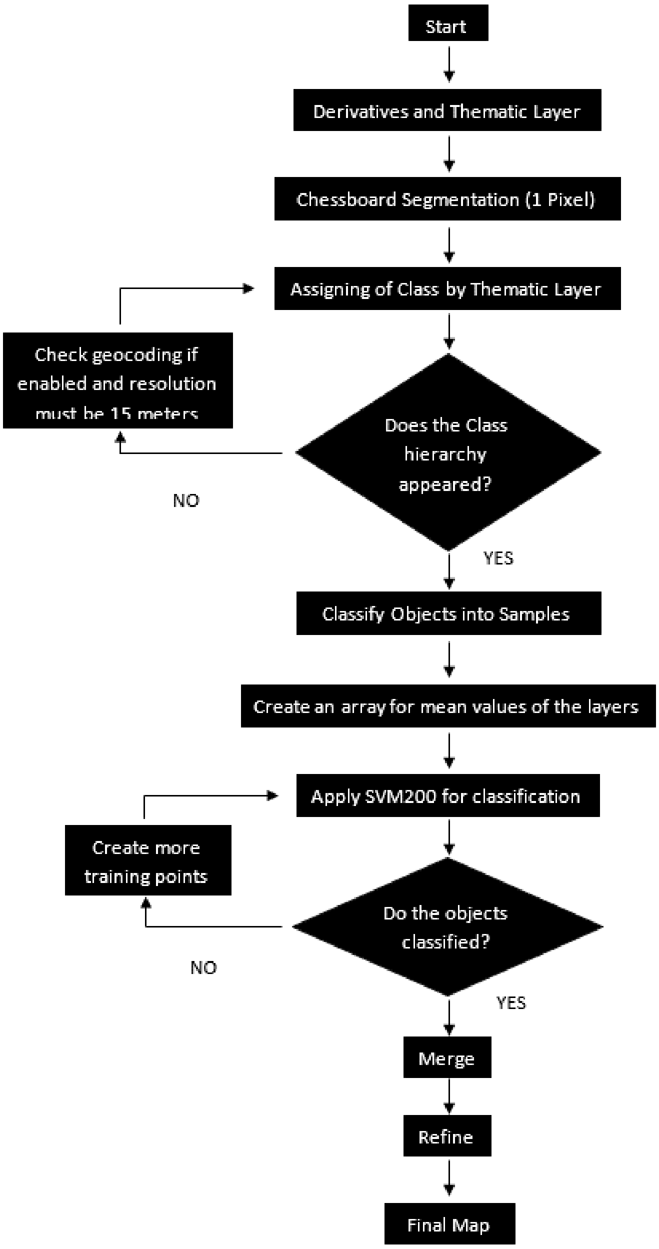

Figure 6. Development of Algorithm using Landsat 8

These derivatives are significant in extracting the classes from Landsat 8. Each derivative corresponds to a unique property that distinguishes its certain features. Derivatives are created using the software Envi 5.1 (Figure 6). The Band Math interface (Figure 6) is used for making expressions in generating derivatives through vegetation indices such as Difference Vegetation Index (DVI), Normalized Difference Water Index (NDWI), Transformed Difference Vegetation Index (TDVI), Green Ratio Vegetation Index (GRVI), Infrared Percentage Vegetation Index (IPVI), Green Difference Vegetation Index (GDVI), Green Normalized Difference Vegetation Index (GNDVI), and Normalized Difference Vegetation Index (NDVI). Vegetation Indices are further discussed in the succeeding pages.

3.4.1. Sampling

This is the crucial process in generating the resource map because the classification will be dependent on the thematic layer. The thematic layer is a merge set of points with a class hierarchy of barren, non-vegetation, other vegetation, coconut, sugarcane, rice field, water, clouds, and cloud shadow. The cloud is included in the classification since there are instances that it cannot be removed even though preprocessing of Landsat was performed.

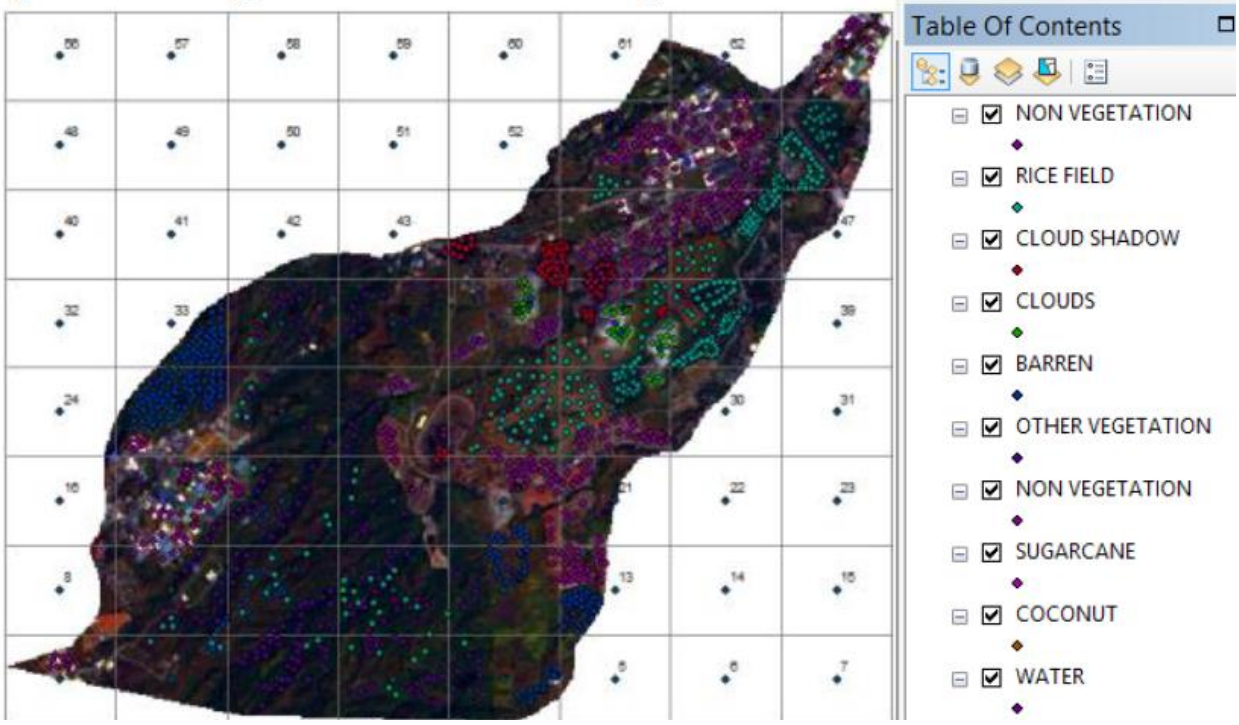

Figure 7. Training and Validation Points

3.4.2. Classification

Classification using low spatial resolution produced is based from the generality in the area. Classification is performed using pixel based analysis using Ecognition Developer software. Classification using pixel based is based from its spectral information provided in each pixel. The 'update array' is an algorithm which creates a list of features which are accessible from rule set levels. It allows repetitively executing of classes. The array created is for extracting features. The mode 'clear' enables clearing of the process. The second process on the update array demonstrates the averaging of floating numbers of each pixel of the layers. Each pixel of the layer has a value and this value is averaged by using Mean. Pixels with darker colors has a value of RGB closer to zero while lighter colors have a value closer to 255. White's RGB value is 255 thus lighter colors have higher values because it approaches the color white. The next process on the update array demonstrates the averaging of floating numbers of each pixel of the layers. Each pixel of the layer has a value and this value is averaged by using Mean. Pixels with darker colors has a value of RGB closer to zero while lighter colors have a value closer to 255. White's RGB value is 255 thus lighter colors have higher values because it approaches the color white.

3.5. Accuracy Assessment

Three crops namely coconut, sugarcane, and rice are to be inspected through ground validation. Municipalities wherein the target classes are abundant have conducted validation, namely: Trece Martires, Maragondon, and Magallanes in Cavite Province.

4. RESULTS AND DISCUSSION

Based from the table above, the folder that contains Area 3 has a lowest accuracy assessment compared to others. It is because other region with rice field was considered as barren.

Table 1. Overall Accuracy of the study area

AREA	OVERALL ACCURACY
Area1	98.5%
Area2	97%
Area3	88%
Area4	99.4%
Area5	99.8%
Area6	99.6%

Table 2. Comparison of the Ground Truth and Extracted features

Coordinates						Validation	Ecognition
Latitude			Longitude			Land Cover	Land Cover
Degree	Minute	Seconds	Degree	Minute	Seconds		
14	12	4	120	45	20	Coconut	Coconut
14	12	4	120	45	21	Coconut	Coconut
14	12	3	120	45	20	Coconut	Coconut
14	12	3	120	45	21	Coconut	Coconut
14	12	2	120	45	20	Coconut	Coconut
14	12	2	120	45	19	Coconut	Coconut
14	12	1.5	120	45	20	Coconut	Coconut
14	12	0.5	120	45	20	Coconut	Coconut
14	12	0.2	120	45	19.55	Coconut	Coconut
14	12	0.282	120	45	19.55	Coconut	Coconut

5. CONCLUSION

The researchers were able to generate the agricultural resource map of Cavite using primarily the Lidar data and the secondary data available. They were able to extract the derivatives that are the fundamental to analyze the lidar data in determining the locations of the three high value crops namely: coconut, rice and sugarcane. Other high value crops existing in Cavite, such as mango and banana, were also classified and included in the map. The algorithm was developed using the SVM (Support Vector Machine) as the classifier. Landsat was the secondary source of data used to generate the agricultural resource map for the municipalities in Cavite that did not have the Lidar data. Other kinds of vegetation were also classified, together with the non-vegetation (houses and buildings). The field validation through the use of Global Positioning System (GPS) is part of the actual method. Marked points and photographs of the crops were recorded and were used as validation points for the accuracy assessment. Results showed that pixel based algorithm provide more accurate result than object based given that the classes are in spatially large area. Nevertheless, object-based classification provided detailed information with implicit information of the classes in the specified area.

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