A ONE-AGAINST-ALL EXTRACTION OF COCOS NUCIFERA AT INDIVIDUAL TREE CROWN LEVEL VIA SUPPORT VECTOR MACHINE CLASSIFICATION USING LIDAR DATA

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ABSTRACT: Philippines is the second largest producer of Cocos nucifera, also known as coconut, in the world, with an average production of 15 billion nuts per year corresponding to a hundred billion pesos. Being one of the major crops in the country, coconut accounts for 26% of the total agricultural land, corresponding to at least 3.5 million hectares. As significant declines in the production have been charted since 2016 due to climate-related incidents and infestations, it is high time that we introduce efficient and accurate data as inputs to resources management in the country. However, managing these much of coconut resources scattered on large geographic area is inefficient if we use data gathered through manual counting, and inaccurate of we resort to rough estimations. As the Philippine government embarks on the acquisition of LiDAR data achieving an equivalent 1 meter grid resolution, this study seeks to achieve classification of coconut trees at the individual tree crown level by performing Object-Based Image Analysis (OBIA) on a simple LiDAR-derived first-return highest-elevation model without the aid of spectral data. Support Vector Machine classification in a one-against-all approach has been implemented for the simplicity of the classification process. The methodology produces highly accurate tree count estimates on selected study sites in San Antonio, Quezon, reaching at least 90% on 16 study areas, without incorporating other remotely-sensed data and without using complex procedures. The outputs of this research suggests that agricultural resources mapping at individual tree level achieves high accuracies even when using LiDAR data alone. This study may also pioneer on “one agricultural class per classification” approach in the improvement of existing agricultural resources maps.

1. INTRODUCTION

In spite of the sufficient efforts rendered, the performance of the Philippine agriculture sector has been charting significant declines (Table 1) particularly in the year 2016 due to climate-related incidents, according to the Philippine Statistics Authority (PSA).

Table 1. Tabulated figures from PSA’s Performance of Philippine Agriculture in 2016

Quarter (2016)	Agriculture Production Performance	Negative Factors
January – March	-4.53 %	Prolonged Dry Spell Typhoons “Lando” and “Nona”
April – June	-2.34%	Prolonged Dry Spell
July – September	+2.98%	(Unaccounted)
October – December	-1.11%	Typhoons “Karen” and “Lawin”

Apparently, the effects of climate change and climate-related disturbances have induced significant variations in the agriculture production. As articulated by the Food and Agriculture Organization of the United Nations (FAO), climate change, with its vast impacts on agricultural productivity, “threatens” the ability of mankind to accomplish sustainable development (2017). Furthermore, it should be accounted for that climate change also induces “changing rainfall patterns, drought, flooding and the geographical redistribution of pests and diseases” on a global scale (FAO, Climate

Change, 2017), as evident in the table above. These scenarios and the ever increasing population call for the improvement of resource assessment and management in the Philippines.

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 A. C., Tamondong, Perez, Ang, & Paringit, 2015). The program, which started July 2014, aims to use the LiDAR datasets in order to extract various natural resources including agricultural, coastal, hydrological, forest and renewable energy. The acquired data achieves an equivalent 1 meter grid resolution and have been used to map natural resources in the Philippines.

This research endeavor, however, has the objective of developing an alternative methodology that focuses on mapping coconut resources at individual tree crown level via linear Support Vector Machine classification. Specifically, this study aims at extracting individual coconut tree crowns using the available LiDAR data in a selected study area.

1.1. Coconut Resources

Philippines is the second largest coconut producer in the world (FAO, Restoring coconut farmers' livelihoods in the Philippines, 2017), with an average production of 15 billion nuts per year[1] and with production values approaching hundred billion pesos (PSA, 2016). In spite of these figures, reports from the Major Non-Food and Industrial Crops Quarterly Bulletin (2016) of the Philippine Statistics Authority (PSA) showed that climate events, such as drought, dry spell and typhoons, have significantly affected the production of the coconut crops in 2016.

Table 2. Declines charted in the production of coconut since 2016

Quarter	Agriculture Production Performance	Negative Factors
2017 Q1	2.3% lower than last year	Dry Spell Drought Cocolisap Infestation
2016 Q4	5.2% lower than last year	Dry Spell Drought Rat Infestation
2016 Q3	7.2% lower than last year	Dry Spell Rat Infestation
2016 Q2	7.0% lower than last year	Dry Spell Typhoon
2016 Q1	5.1% lower than last year	Extreme Heat Dry Spell Typhoon

Way back in 2013, when typhoon Haiyan struck the Philippines, coconut trees that were “destroyed or damaged” reached an estimated 44 million trees. Being one of the major crops in the Philippines, coconut accounts for 26% of the total agricultural land, corresponding to at least 3.5 million hectares of coconut areas. Monitoring and managing these much of resources scattered on a large geographic area would be inefficient if we conduct manual counting, and inaccurate if we resort to rough estimations.

The availability of high resolution remote sensing (RS) data has been found to be an effective solution in dealing with such problems that involve geospatial concepts. In fact, the Philippine government utilized the technology known as Light Detection and Ranging (LiDAR) in producing three-dimensional maps. Moreover, by expounding on the information that can be obtained from LiDAR data, an offshoot program known as Phil-LiDAR 2[2] has been created, tasked to extract natural resources features, including agricultural, coastal, forest, hydrological and renewable energy from RS data (Blanco A. , et al., 2016).

Current literature describes that current RS data allow not only the mere extraction of features on earth, but also the estimation of important quantities that greatly contribute in resources management. In focusing on the coconut industry alone, we can already pinpoint coconut plantations and determine their total crown projection areas using landuse/landcover maps produced out of the LiDAR data. However, in order to produce good estimates, the classification image must be of the individual tree crown (ITC) level. In practice, the design of the methodology in achieving the ITC level ponders on some major considerations, such as the cost of high resolution RS data and the complexity of the image processing methods.

[1] This is calculated by averaging the nut production from 2011 to 2015.
[2] Phil-LiDAR 2 was created as a different venture while the former DREAM has become Phil-LiDAR 1

1.2. Level of Detail in RS/GIS Products

The level of detail that can be extracted from remote sensing images greatly depends on the resolution of the data. The spatial resolution of the data, which describes the real-world dimensions contained inside a pixel, limits the dimensions of the objects that can be "seen" in the data. The higher is the resolution, the more capable the system is in extracting smaller features.

Aside from the resolution, data fusion increases the accuracy of classification particularly in identifying tree species and delineation of individual tree crowns (Gulbe, 2015). This has been supported by the study conducted by Lee, et al. in 2016, concluding that the accuracy of tree species mapping can be improved by combining LiDAR and hyperspectral imagery. In essence, data fusion refers to the combination of information out of various domains. In general, data fusion occurs in any of the following parts of the process: measurement, feature and decision (Gulbe, 2015). Using single input data alone may not produce the desired output and performance. When Gulbe used LiDAR data alone, the results were not acceptable "due to low point density for a complex forest structure" (2015).

Various input layers can also be derived from a single RS data by exploiting on the parameters. The study performed by Ferreira, et al. in 2014 used vegetation indices layers extracted from hyperspectral data to improve the individual tree crown delineation process. In essence, the quality of the image processing outputs greatly depends on the quality of the input datasets.

1.3 Object-Based Image Analysis

Object-based image analysis (OBIA) has been introduced to improve image processing and eliminate the speckles that are inherent in the pixel-based process. Instead of involving pixel classification, OBIA works on objects, which are outlined regions with homogeneous properties (Yadav, Rizvi, & Kadam, 2015), with segmentation being the heart of the process.

Segmentation refers to the method of generating object outlines. It refers to the creation of objects that are an aggregation of pixels with similar features. Figure 1 shows delineation of objects applied in an elevation layer. Pixels of similar elevation values aggregate together, forming the objects.

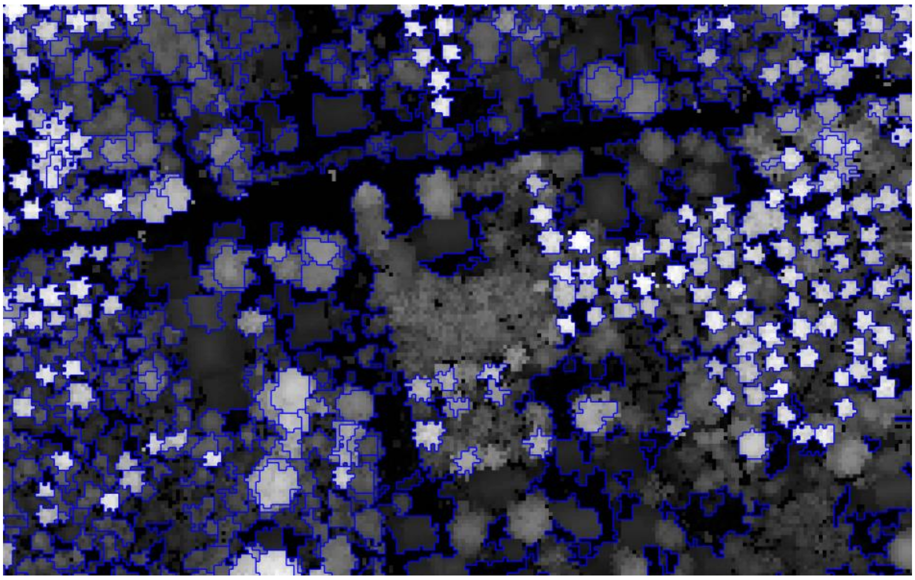

Figure 1. Image scene containing delineated objects, viewed using eCognition

Kumar, et al. discussed that image segmentation can be categorized depending on the approach, such as thresholding, region-based, edge-based, ANN-based, PDE-based and Fuzzy-based (2016). Landcover mapping is fundamental in utilizing RS data for natural resources management. While segmentation is the core of the OBIA process, derivation of information from RS images relies on "robust classification methods" (Maulik & Chakraborty, 2017). Image classification involves "image pre-processing, the detection and extraction of an object, feature extraction, selection of training samples, selection of suitable classification techniques, post-classification processing and accuracy assessment."

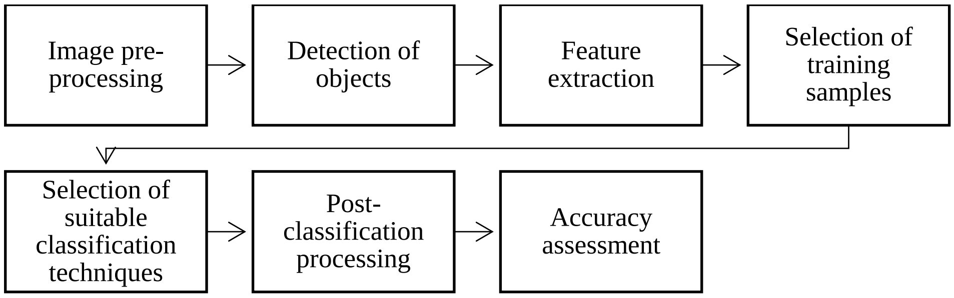

Figure 2. Major steps in image classification (Maulik & Chakraborty, 2017)

Machine learning plays an important role in the context of image classification. In RS application, machine learning algorithms eliminate the task of manual selection of land cover classes. Identification of suitable machine learning algorithms considers effectiveness and efficiency.

Machine learning can be unsupervised and supervised. Advanced classification procedures use supervised methods in which the training sets of examples are used in identifying class boundaries. Common supervised learning methods are nearest neighbor, decision tree and Support Vector Machine (SVM) algorithms.

The Support Vector Machine (SVM) classifier is one of the most commonly preferred algorithms in RS applications due to its “good classification performance with high-dimensional data” (Baldeck & Asner, 2015) and it is even labeled as the top-performing classifier algorithm when dealing with hyperspectral data in recent studies.

While SVM methods were originally tested in the classification of as much classes as possible in an image scene, research objectives that deal with one or a few classes are not uncommon.

1.4 Delineation of Tree Crowns

Tree species classification and individual tree information critically relies on how well the individual trees are delineated (Wu, et al., 2016). Manual outlining of tree crowns is able to sufficiently achieve desirable results using images with high spatial resolutions. This method, though, is “labor intensive and therefore unfeasible over large areas” (Ferreira, et al., 2014).

As the segmentation seeks to achieve one crown polygon for each of the trees, failure to do so may lead to either an over-segmentation or an under-segmentation. An over-segmentation occurs when a single tree is detected as multiple crowns. It may occur when branches and sub-crowns of a single tree resembles other smaller trees (Hu, Li, Jing, & Judah, 2014). Under-segmentation, however, happens when adjacent trees are falsely detected as a single tree. Table 3 summarizes recent researches on individual tree crown delineation. Almost all ITC methodologies found in the literature focus on forest sites. The RS data, algorithm used and the respective accuracies have also been tabulated.

Table 3. Individual tree crown delineation related studies and their accuracies

Study	Site	RS Data (resolution)	Algorithm/Method	Accuracy
Yang, He, & Caspersen (2014)	Deciduous forest	ADS40 Multispectral aerial image (0.4 m)	Watershed algorithm	90%
Wu, et al. (2016)	Coniferous forest	LiDAR (7.76 pts/m^2)	Localized contour tree method	94.21%
	Coniferous forest	LiDAR (12.49 pts/m^2)		75.07%
Zaki, Latif, Zainal, & Zainuddin (2015)	Tropical forest	Worldview-2 satellite image (0.5 m)	Watershed algorithm	82.6%
Liu, Im, & Quackenbush (2015)	Coniferous forest	LiDAR (~10 pts/m^2)	Fishing Net Dragging algorithm	79%
	Mixed forest			78%
	Deciduous forest	LiDAR (~7 pts/m^2)		74%
Gulbe (2015)	Natural forest	Multispectral aerial image (0.5 m)	Region growing method	72% 75%

		LiDAR (4 pts/m^2) fused with multispectral image		
Yang J. , He, Caspersen, & Jones (2017)	Uneven-aged, mixed-broadleaf forest	ADS40 Multispectral aerial image (0.4 m)	Watershed algorithm	51% 69%
Lee, et al. (2016)	Deciduous forest	LiDAR (6 pts/m^2) and hyperspectral image (361 spectral bands, at 1.2 m)	LiDAR point cloud-based clustering method	65.8%
Lindberg, Eysn, Hollaus, Johan, & Pfeifer (2014)	Hemi-boreal forest	Full waveform LiDAR (7 pts/m^2)	Watershed algorithm	71%
Hu, Li, Jing, & Judah (2014)	Mixed forest Deciduous forest	LiDAR (40 pulses/m^2)	Watershed algorithm	74% 72%
Ferreira, et al. (2014)	Semi-deciduous species on tropical forest	ProSpecTIR-VS hyperspectral image (357 bands)	Region growing algorithm	55% 56% 70%

Although individual tree crown delineation methods have claimed promising results, (Kaartinen, et al., 2012) the "criteria for tree detection and extraction can be different" depending on the application, which means that there is variability in the methods that can be applied. For instance, the region growing approach has the advantage in that it "can make use of all the spectral bands provided by the multispectral images" but the results may contain stick-shape segments (Yang, He, & Caspersen, 2014). Currently, researchers are still working on increasing the accuracies of ITC methodologies by improving the existing methodologies found in the literature.

2. METHODOLOGY

2.1. Study Area and Materials

Flight mission "Laguna_Blk18VWs_20140425" crosses the municipality of San Antonio in the province of Quezon. 16 LiDAR tiles are selected for processing, with each tile covering a 1-by-1-km grid. These 16 tiles completely cover barangays Niing, Bagong Niing and Poblacion.

The province of Quezon has been selected as it is one of the top producers of coconuts in the Philippines. The municipality of San Antonio is picked due to considerations on the variability of features, safety and accessibility. 16 tiles have been used to fit in the study time frame.

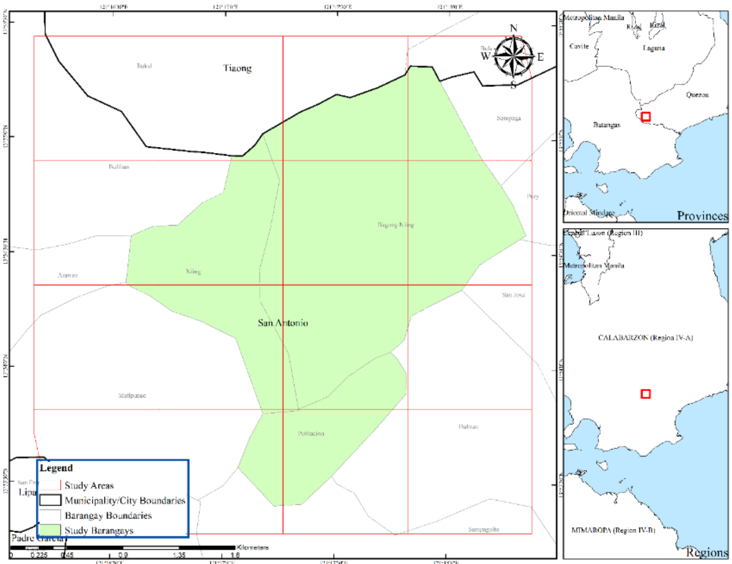

Figure 3. Selection of LiDAR data tiles in the study area

2.2. Methodological Workflow

The workflow implemented in the study is shown Figure 4. The overall workflow starts with the selection of the LiDAR datasets. Then, the elevation values are rasterized such that every pixel provides height values of features relative to the ground. The raster datasets are loaded in the eCognition software in the implementation of Object-Based Image Analysis. First, a series of segmentation procedures are executed until the individual trees are delineated. The field data samples are loaded as a vector file and are used to train the SVM classifier algorithm. The training is implemented on only two classes, namely Coconut and Not-Coconut classes.

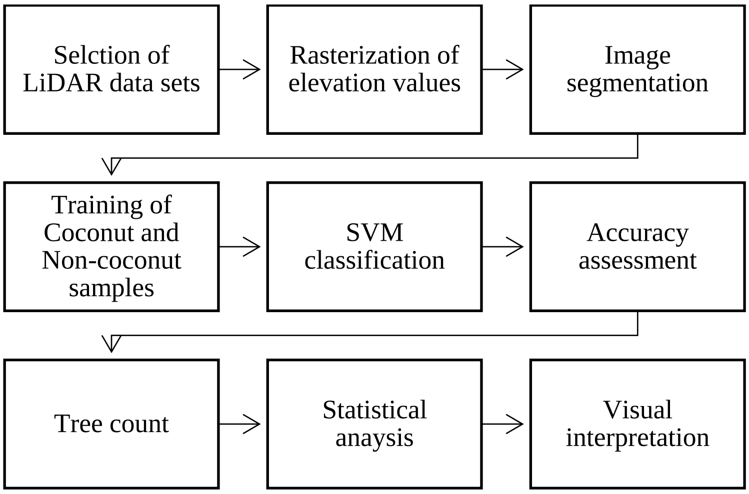

Figure 4. Methodological framewrok implemented for the study

The resulting classified image layers are assessed using another set of sample data sets labeled as validation points. These data points are used in the accuracy assessment of the 16 eCognition projects. After ensuring that the accuracies of the classification are at tolerable levels, the tree count is implemented.

Statistical analysis is performed among the tree count extracted from the classified layers and the tree count information from manual counting. The root mean square error is determined and the p-value interpreted. Visual interpretation tests whether the generated vector files are useful thematic map layers.

2.3. Elevation raster data generation

The methods in the generation of elevation rasters are crucial in the classification, especially when complex procedures and workflows are not necessary in the study. In the extraction of elevation values, Figure 5 shows the series of steps used to generate the raster inputs to the segmentation process. As shown, the LAS tiles undergo conversion to the EGM08 model for considerations on the calibration of the datasets. Then, extraction of LiDAR first returns is implemented to acquire the points that mostly define the surface of canopies. Then, highest elevation is chosen since and they are recalculated relative to ground points. Eventually, the values form raster data sets.

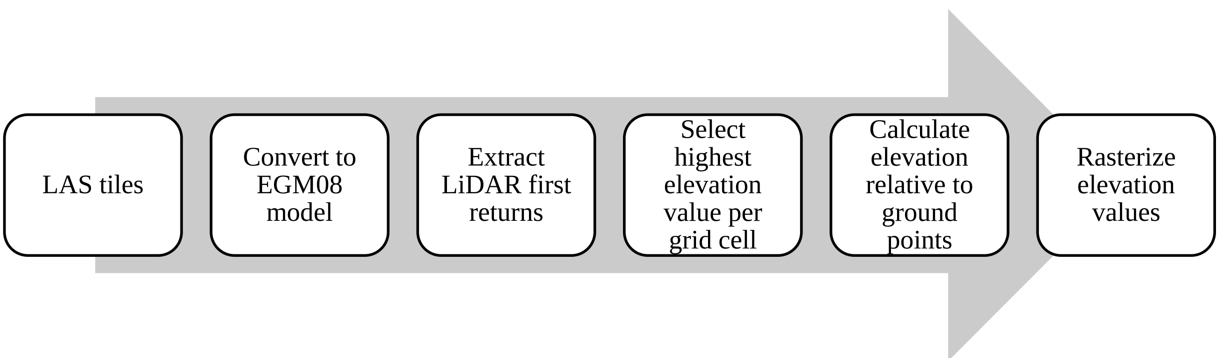

Figure 5. Workflow used in the creation of LiDAR-derived elevation layer

2.4. Image Segmentation

The series of segmentation algorithms applied is shown in Figure 6. The parameters used are chosen with most considerations on coconut trees. Multi-threshold algorithm was used to eliminate in the classification process those features that have zero elevation. Contrast-split segmentation has been applied for the separation of ground and non-ground features since there is no particular value that we can just randomly select to separate them from all the other classes.

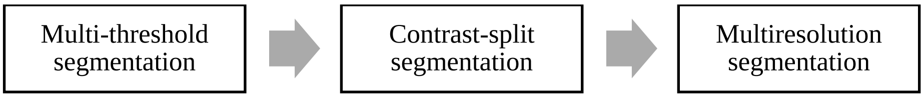

Figure 6. Segmentation algorithms executed in delineating objects

2.5. Sample data sets for training and validation

Figure 7 depicts the distribution of samples in the 16 study sites. Two 100m-by-100m grids are chosen for the selection of training data sets for each of the study areas. The training samples consist of two classes, namely Coconut and Not Coconut. The features used have been limited to elevation, area in pixels and elliptic fit, for simplicity.

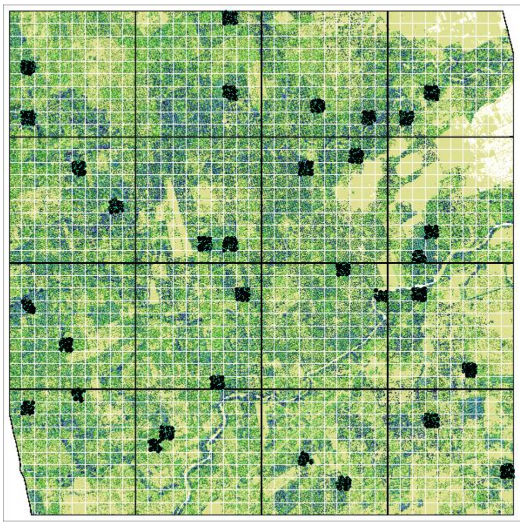

Figure 7. Training samples in 100m-by-100m grids

Similarly, the samples for validation are selected from two 100m-by-100m grids but with locations not coinciding with the grids of the training samples.

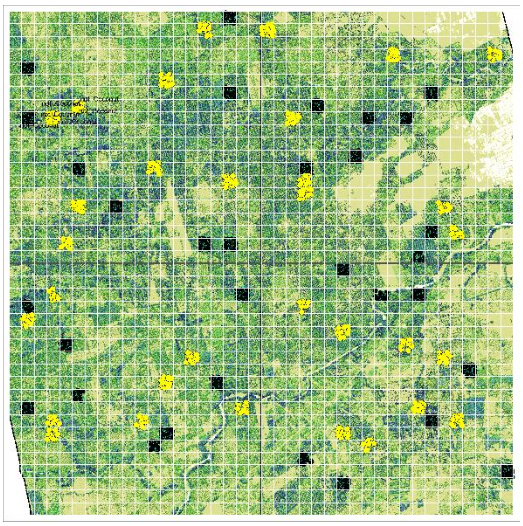

Figure 8. Samples for validation (in yellow)

3. RESULTS AND DISCUSSION

3.1. Accuracy Assessment of SVM Classification

Using the sample data sets depicted in Figure 8 as validation data, accuracy is performed by creating TTA mask out of these samples. The generated accuracy levels are tabulated in Table 4, with producer, user, and overall accuracy indices.

Table 4. Overall accuracies of the classified layers for all the 16 study sites

Study Area	LAS No.	Class	Producer	User	Hellden	Short	KIA Per Class	Overall Accuracy	KIA
1	Pt000222	Coconut	1.0000	0.9427	0.9705	0.9427	1.0000	0.9623	0.9184
		Not Coconut	0.9008	1.0000	0.9478	0.9008	0.8492		
2	Pt000224	Coconut	0.8790	0.9645	0.9198	0.8515	0.7267	0.9062	0.8075
		Not Coconut	0.9490	0.8328	0.8871	0.7971	0.9085		
3	Pt000226	Coconut	0.7896	0.8788	0.8318	0.7121	0.6396	0.8521	0.7004
		Not Coconut	0.9060	0.8330	0.8680	0.7667	0.7742		
4	Pt000227	Coconut	0.8894	0.9874	0.9358	0.8794	0.7647	0.9282	0.8549
		Not Coconut	0.9837	0.8615	0.9186	0.8494	0.9693		
5	Pt000228	Coconut	0.8739	0.9122	0.8927	0.8061	0.7666	0.8992	0.7976
		Not Coconut	0.9224	0.8880	0.9049	0.8263	0.8313		
6	Pt000229	Coconut	0.9195	0.8946	0.9069	0.8296	0.8613	0.9229	0.8411
		Not Coconut	0.9252	0.9434	0.9342	0.8765	0.8218		
7	Pt000264	Coconut	0.8797	1.0000	0.9360	0.8797	0.7324	0.9247	0.8455
		Not Coconut	1.0000	0.8325	0.9086	0.8325	1.0000		
8	Pt000265	Coconut	0.8828	0.9685	0.9237	0.8581	0.8037	0.9355	0.8681
		Not Coconut	0.9773	0.9133	0.9442	0.8943	0.9436		
9	Pt000266	Coconut	0.9504	0.8687	0.9077	0.8311	0.8833	0.8985	0.7954
		Not Coconut	0.8410	0.9387	0.8872	0.7973	0.7234		
10	Pt000267	Coconut	0.8974	0.9571	0.9263	0.8627	0.7867	0.9209	0.8412
		Not Coconut	0.9501	0.8819	0.9148	0.8429	0.9039		
11	Pt000268	Coconut	0.9202	0.8696	0.8942	0.8086	0.8539	0.9066	0.8107
		Not Coconut	0.8963	0.9373	0.9164	0.8457	0.7716		
12	Pt000269	Coconut	0.9108	0.9666	0.9378	0.8830	0.7658	0.9207	0.8286
		Not Coconut	0.9397	0.8462	0.8905	0.8026	0.9026		
13	Pt000270	Coconut	0.9517	0.9694	0.9605	0.9239	0.8877	0.9545	0.9070
		Not Coconut	0.9585	0.9348	0.9465	0.8985	0.9272		
14	Pt000271	Coconut	0.9078	0.9562	0.9314	0.8716	0.8025	0.9249	0.8485
		Not Coconut	0.9468	0.8891	0.9170	0.8467	0.9001		
15	Pt000272	Coconut	0.9490	0.9739	0.9613	0.9255	0.8985	0.9609	0.9219
		Not Coconut	0.9734	0.9481	0.9606	0.9242	0.9465		
16	Pt000286	Coconut	0.9432	0.9836	0.9630	0.9286	0.8857	0.9619	0.9238
		Not Coconut	0.9826	0.9400	0.9608	0.9246	0.9654		

Accuracy levels for all study areas have been satisfactory. The producer accuracies on average are reaching above 90% for all study areas. Although we are using only two classes as inputs to the SVM classifier, the results suggest that the one-against-all approach can achieve at least 90% overall accuracy levels.

Moreover, the producer accuracies are a direct measure of the accuracy of coconut count.

3.2. Estimated Coconut Tree Count

Estimated and manually counted coconut trees are tabulated in Table 5**.** Apparently, majority of the count estimates are less than the manually generated counts. However, we can still see that the estimates are useful in predicting the actual values of the coconut trees in the sampling plots.

Table 5 Tree count accuracy assessment: vector count versus manual count

Study Area	**Source LAS number**	**Count**	**Manually Counted**

1	Pt000222	277	284
2	Pt000224	342	337
3	Pt000226	221	211
4	Pt000227	174	181
5	Pt000228	141	137
6	Pt000229	195	187
7	Pt000264	249	228
8	Pt000265	176	189
9	Pt000266	237	224
10	Pt000267	253	247
11	Pt000268	280	263
12	Pt000269	289	259
13	Pt000270	265	260
14	Pt000271	241	254
15	Pt000272	262	251
16	Pt000286	286	264

By regression we can determine the agreement between the estimates and the actual values for the count. Regression statistics are summarized in Table 6. The computed R Square value is 0.94, proving that the estimates agree with the manually counted values in a linear manner.

Table 6 Regression statistics for coconut count

Regression Statistics	
Multiple R	0.971436
R Square	0.943688
Adjusted R Square	0.939665
Standard Error	11.70505
Observations	16

The standard error is 11.7 which can sometimes be corrected using some bias constant values.

4. CONCLUSION

The one-against-all approach in classifying coconut trees in 16 study areas in San Antonio, Quezon has been effective in differentiating coconut features from non-coconut features without the need to identify the other classes. Around 90% accuracy levels are achieved using SVM classification algorithm through sample training datasets on 100m-by-100m grids for each of the study areas.

In addition, the proposed segmentation procedures is able to achieve the individual tree crown level for coconut trees and is achieving accurate estimates in 16 study sites, with a good R Square value for estimate and manually counted data regression.

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