ASSESSMENT OF LIDAR-DERIVED HEIGHT METRICS FOR MAPPING MANGROVE FOREST USING OBJECT-BASED METHOD

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ABSTRACT: Object-based method in mangrove mapping has been widely used recently, testing various classifiers on different datasets. With the scarcity of available imagery data, this study focuses on classifying mangroves from LiDAR data only. It has been found that even without spectral data, LiDAR data alone can be used to map mangrove forests. Upon the inclusion of common forestry metrics and other height information from LiDAR data as input features, confusion among classes was observed in doing Support Vector Machine (SVM) classification. Thus, assessment of input features and the variables derived from them is essential. In this study, a Decision Tree (DT) was constructed to determine the importance of each variable derived from fifteen LiDAR height metrics. The input layers was filtered for SVM classification based on the results of the DT. The effectiveness of the method was assessed in five different locations. Using the method in this study, the relevant features derived from the LiDAR height metrics were identified. At least 90% reduction in the number of variables was achieved. It was established that reduction in the training and classification time of SVM resulted when the filtered input variables were used, without sacrificing the accuracy and kappa index of agreement. At least 92% reduction in time for SVM training and classification was achieved, compared with using all the available variables. Hence, DT can be a useful pre-classification process for SVM.

1. INTRODUCTION

In July 2014, the Philippines embarked on the Phil-LiDAR 2 Program: National Resource Inventory of the Philippines Using LiDAR and other Remotely Sensed Data. The Phil-LiDAR 2 is a three-year program funded by the Department of Science and Technology (Blanco, Tamondong, Perez, Ang, & Paringit, 2015). The program aims to use the LiDAR datasets in order to extract various natural resources including agricultural, coastal, hydrological, forest and renewable energy.

This study focuses on the objective of developing methodology for mapping coastal resources. In particular, this study is aimed at assessing LiDAR-height derivatives useful for mangrove mapping by performing feature selection method.

1.1 Importance of Mangrove Mapping

Mangroves are significant part of the ecology since they contribute to the protection of coastal areas or communities from typhoons and storm surges, responsible for sediment trapping and erosion control along the riverbank and shoreline, regulate flooding, help in nutrient recycling, and provide marine or wildlife nurseries and habitat (Primavera & Esteban, 2008).

However, mangrove forests depleted quickly in the past years due to development done along coastal areas, aquaculture and agriculture land conversion, pollution and overexploitation of mangrove resources for the production of charcoal, firewood, and timber (United Nations Environment Programme, 2014).

Due to the increasing realization of the importance of mangrove forests, the CALABARZON Region have been implementing rehabilitation, management, and protection of mangroves since 2011. This includes programs like reversion of abandoned fishpond to mangrove, maintenance and protection of established mangrove plantations and plantation establishment and rehabilitation of denuded/degraded ecosystem (Department of Environment and Natural Resources (CALABARZON Region), 2014).

Normally, the inventory and monitoring of these mangrove plantations is through surveying and field validation. One way that provides an advanced and easy way of site assessment is through mangrove mapping which uses remote sensing techniques. Mangrove mapping makes it possible to monitor accurate changes of mangrove forests over time especially when there is deforestation or aquaculture activity. It may also be used when making a development plan for the restoration/rehabilitation and maintenance of mangrove areas.

A previous study conducted mangrove mapping through remote sensing for the damage and recovery assessment of mangrove areas in the Philippines especially along the path crossed by Super Typhoon Haiyan (Long J. , Giri, Primavera, & Trivedi, 2016).

1.2 Status of Mangroves in Batangas and Quezon

There has been an increase in aquaculture fish production in the Philippines, particularly in Batangas and Quezon province from 27,235 to 70,799.5 metric tons in the year 2000-2012 (Philippine Statistics Authority, 2016). This contributed to a rapid depletion of mangroves forest in the country due to conversion of mangroves areas to fishponds to support the fisheries production. A total of 10.5% decrease in mangrove forest in the country was observed from 1990-2010 (Long, Napton, Giri, & Graesser, 2014). In Calatagan, Batangas, roughly 144 hectares of mangroves forest cover was converted into fishponds (Provincial Government of Batangas, PEMSEA, 2008).

In 2007, ground validation in Region IV-A covering Cavite, Laguna, Batangas, Rizal and Quezon (CALABARZON) was conducted to measure the extent of the remaining mangroves forest in the area. A total of 11,685.7 hectares of mangroves have been found with 822.94 hectares in Batangas and 10,830.1 hectares in Quezon province (Department of Environment and Natural Resources, 2013). Another series of ground validation was conducted in the region in 2011. An additional 70 hectares of mangrove area were validated in Quezon and 27.9 hectares in Batangas (Department of Environment and Natural Resources, n.d.)

Continuous effort has been made to conserve and rehabilitate the biodiversity of Mangroves in the typhoon-prone coastal areas of Batangas and Quezon province. In fact, a total of 1,000 hectares of mangrove was initially rehabilitated in Batangas and Quezon (Department of Environment and Natural Resources, 2016). Mangroves rehabilitation was led by Department of Environment and Natural Resources (DENR) with the cooperation of Local Government Units (LGUs), Non-government Organization (NGOs) and various private organizations.

1.3 Previous Works on Mangrove Mapping

In the earlier studies, both SPOT XS and Landsat TM have been used in regularly mapping mangroves. In the study of Green, et al. (1998), they experimented different combination of sensor like Landsat TM, SPOT XS, Compact Airborne Spectrographic Imager (CASI) and image processing method like NDVI Image, Unsupervised or Supervised classification, and PCA/band ratios for mangrove mapping. They discovered at that time that the most accurate combination if the discrimination between mangrove and non-mangrove vegetation is required over a large area at relatively low time and money cost is the use of Landsat TM and Principal Component Analysis (PCA)/band ratio image processing (Green, Clark, Mumby, Edwards, & Ellis, 1998).

Landsat imagery with Iterative Self-Organizing Data Analysis Techniques (ISODATA) clustering may also be used in getting the extent of mangrove forests. The sixty-one 30-meter resolution Landsat images were classified using ISODATA algorithm which is an unsupervised classification technique (Long & Giri, 2011).

Heumann (2011a) reviewed other remote sensing technology used in mapping mangrove forests. Even though pixel-based classification of Landsat, SPOT, and ASTER imagery have been widely applied in mangrove mapping, more recent types of images such as very high resolution (VHR), Polarmetric Synthetic Aperture Radar (PolSAR), hyperspectral, and LiDAR systems are being used for classification via techniques such as Object Based Image Analysis (OBIA), spatial image analysis (e.g. image texture), Synthetic Aperture Radar Interferometry (InSAR), and machine-learning algorithms which yields to a more reliable and detailed mangrove forests characterization (Heumann, 2011a).

Another study demonstrated the use of object-based image analysis (OBIA), support vector machine (SVM), and Worldview-2 sensor in accurately mapping fringe and true mangroves species overcoming the limitation of traditional remote sensing approaches because of coarse spatial resolution of images (Heumann, 2011b). However, this study showed the necessity for greater spectral resolution to distinguish between individual species. Heumann (2011b) recommended the use of Light Detection and Ranging (LiDAR) to improve the spectral properties and enhance the segmentation of the image based on canopy structure.

LiDAR-derived data such as Canopy Height Model (CHM), average intensity and number of returns arithmetic can be used in mangrove forest mapping through the use of OBIA and SVM in the case of Calatagan, Batangas. In this study, the accuracy assessment based on test and training area (TTA) mask yielded an overall accuracy of 0.91 with a Kappa Index of Agreement of 0.85 (David & Ballado, 2015b).

Even with the use of LiDAR derivatives and orthophoto for SVM classification, confusion among classes were reported by Phil-LiDAR 2 partner institutions, testing various classifiers in different locations (David & Ballado, 2015a; Jalbuena, et al., 2015; Pada, et al., 2015) With the unavailability of orthophoto for many LiDAR flight missions, classification can be even more challenging, resulting to slight decrease in accuracy (David & Ballado, 2015b). Classifiers can perform poorly because of the presence of redundant and irrelevant data.

2. METHODOLOGY

2.1 Study Area and Materials

The study area covers the extent of mangrove areas located in the provinces of Batangas and Quezon, mainly the coastal zones of Calatagan (13°49'36" N 120°39′26" E) and Lian (13°58'02" N 120°36′54" E) and, the coastal zone of Infanta (14°41'29" N 121°38′58" E). Aquaculture ponds neighboring mangrove forests are also common in these municipalities.

(a) Calatagan, Batangas (b) Lian, Batangas (c) Infanta, Quezon

Figure 1. Google Earth image showing the three study sites (municipal boundaries from National Statistics Office).

Calatagan, Batangas is a 2nd class municipality with a land area of 106.33 sq. km while Lian, Batangas is a 3rd class municipality with a land area of 91.27 sq. km both lying in the West Philippine Sea. Infanta, Quezon known as the "Gateway to Pacific", is a 1st class municipality that lies along the coast of the Pacific Ocean with a land area of 94.76 sq. km. These three municipalities have more than 98% LiDAR data coverage that was obtained in 2014 by the Disaster Risk and Exposure Assessment for Mitigation (DREAM^{TM}).

Table 1. LiDAR-derived height metrics.

Acronym	Meaning
CHM	Canopy Height Model derived using the algorithm of Khosravipour, et al. (2013)
CHM MAX	Focal statistics showing maximum value of the CHM raster computed with a rectangular 3x3 neighborhood
CHM STD	Focal statistics showing standard deviation of the CHM raster computed with a rectangular 3x3 neighborhood
DSM	Digital Surface Model
DTM	Digital Terrain Model
nDSM	Normalized Digital Surface Model
SLOPE	Computed gradient of the DSM raster
HT KUR	Kurtosis of height based on LiDAR points
HT MAX	Maximum value of height based on LiDAR points
HT MIN	Minimum value of height based on LiDAR points
HT P01	1st Percentile of height based on LiDAR points
HT P99	99th Percentile of height based on LiDAR points
HT QAV	Quadratic average of height based on LiDAR points
HT SKE	Skewness of height based on LiDAR points
HT STD	Standard deviation of height based on LiDAR points

To process the LiDAR point clouds, LAStools software was used to derive the digital terrain model (DTM), digital surface model (DSM), slope and popular forestry metrics, thereby creating raster layers needed for the object-based mangroves classification. The object-based image analysis was carried out using eCognition, while ArcMap was used for GIS-related processes.

Table 1 details the layers used in the classification. From the 15 LiDAR-derived height metrics, statistical variables were calculated including mean, standard deviation, 50th quantile and mode, amounting to 60 input variables. Note that each statistic is computed per segmented object.

2.2 Feature Selection

Relying solely on LiDAR derivatives for mangrove mapping, many variables (e.g. 60 for this case) can serve as input for SVM training; in which unknowns are the redundant and irrelevant variables. Hence, a feature selection technique is necessary for this problem. Generally, there are three goals for implementing a feature selection technique: (1) to improve prediction performance of the predictor; (2) to provide faster and more cost-effective predictors; and (3) to provide better understanding of underlying process that generated the data (Guyon & Elisseeff, 2003).

Although SVM performs well, a major drawback is its computational cost, particularly occurring on the training phase (Cristianini & Shawe-Taylor, 2000; Chang, et al., 2010). This happens because training the classifier requires solving a quadratic programming problem (QPP), which is a computationally expensive task (Cervantes, Farid García Lamonta, Mazahua, & Ruíz, 2015). Cervantes et al. (2015) further noted that solving the QPP becomes impractical when the data sets are huge because the amount of time and memory invested is between $O(n^2)$ and $O(n^3)$.

Recently, studies are focusing on various data reduction techniques for SVM classification. Reduction techniques prior to SVM classification have been tested by Georgescu, et al. (2010), including Principal Component Analysis, Partial Least Squares, Structurally Random Matrices and Orthogonal Matching Pursuit.

Decision Tree, a machine learning algorithm widely used in data mining, has been a tool for data reduction. DT is a binary tree wherein a series of decisions are made to segment the data into homogeneous subgroups (eCognition, 2014). The decision tree is built by undergoing a recursive process; sorting data from a node, where a test is made based on an attribute, branching to another node, where another test is made, until it reaches a final classification at the leaf node (Mitchell, 1997).

A novel algorithm was developed by López-Chau, et al. (2012) to select the most important sample from training data by guiding the sample selection giving more chance to be selected to those examples that are on the boundaries of clusters discovered by a decision tree. Although the size of training data was reduced, there was a slight decrease in the accuracy of the classifier; but they claimed that it works well for large datasets.

More recently, Cervantes, et al. (2015) improved their previous work by applying a data filter based on a decision tree that scans the entire data and obtains a small subset of data points. They also noted that the proposed algorithm works very fast even with large data sets and that it outperforms the current state of the art SVM implementations without substantial reduction of accuracy.

The built decision tree is not only used for prediction, but also for further data analyses. An important property of the constructed decision tree is its ability to compute the importance value (relative decisive power or information gain) for each feature (Mitchell, 1997; OpenCV). This can be performed in eCognition by querying the attributes of the trained DT using Query operation.

Aside from its applications in remote sensing, DT has been a popular choice as a pre-processing step for SVM classification, as discussed above. For this study, five minimum number samples per node was arbitrarily chosen for all the decision trees. Furthermore, we applied a five-fold cross validation in order to address the issue of having either too few splits (poor predictive accuracy) or too many splits (complex tree).

In a cross-validation procedure, the DT is computed from the learning samples and its predictive accuracy is tested by test samples. A poor cross-validation results when the costs for the test sample exceed the costs for the learning sample; thus, a different sized tree might cross-validate better (eCognition, 2014).

Different from the works of López-Chau, et al. (2012) and Cervantes, et al. (2015), this study aims to identify the relevant variables derived from LiDAR height metrics useful for mangrove mapping by using Decision Tree. In other words, it aims to filter the variables and not the training samples. The filtered variables serve as input to the SVM classification.

2.3 Procedures

Fig. 2 shows the workflow developed in this study. Considered as the building block of OBIA, image segmentation is an important step such as analysis. Blaschke (2010) defines segments as regions which are generated by one or more criteria of homogeneity in one or more dimensions (of a feature space) respectively. Various segmentation algorithms are available such as multi-resolution, multi-threshold, chessboard, quad-tree, and contrast-split, to name a few. These algorithms output objects which are relatively homogenous and semantically significant group of pixels.

Training samples of mangrove, other vegetation and non-vegetation were created in ArcMap. After running the Decision Tree algorithm in eCognition, suggested layers according to its importance were used in performing SVM. To compare the result of DT-based SVM (SVM_{DT}), SVM using all variables was also performed (SVM_{ALL}).

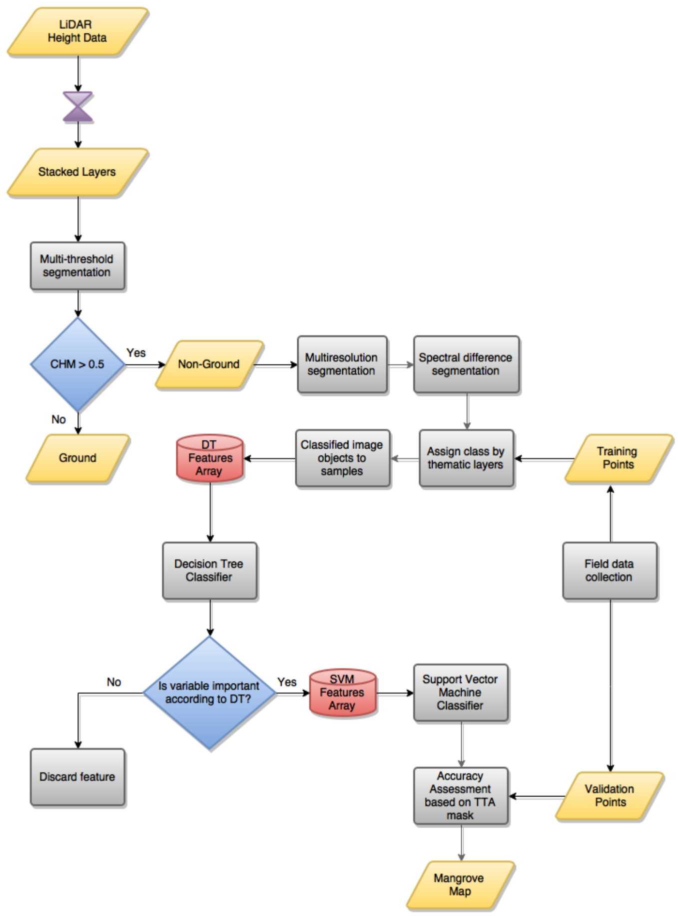


Figure 2. Flowchart showing the procedures in mangroves extractions.

3. RESULTS AND DISCUSSION

In object-based image analysis, segmentation plays an important part as it affects the prediction success of the classifier, the separability of the classes, the accuracy of the classification and the overall visual appeal. A multi-scale segmentation approach was applied using different algorithms. The CHM (0.5m resolution) enabled the separation of ground (CHM ≤ 0.5m) and non-ground (CHM > 0.5m) objects using multi-threshold segmentation. There were small objects with minor errors in CHM due to triangulation. As a solution, nDSM (1m resolution) can be used to correct them, provided that it is does not have triangulation errors.

The use of multi-resolution segmentation on CHM MAX (scale = 20, shape = 0.1, compactness = 0.9) in segmenting non-ground objects produced agreeable results, with few under-segmentation. Over-segmentation on clustered trees was apparent since the scale parameter used is relatively low. Nevertheless, this paper does not aim to do individual tree crown delineation. By applying spectral difference segmentation, more meaningful objects were created by merging neighboring objects whose maximum spectral difference based on CHM was 0.25.

The Decision Trees built for each municipality can be found on Fig. 1-3; and, the table of importance generated from the built DTs can be found on Table 1. For the three different locations, it can be observed that variable from the DTM layer topped the list, gaining the most decisive power. This can be attributed to the fact that mangroves are commonly found on flats near the coast, having lower values of DTM; while some selected samples of other vegetation and non-vegetation are located to the areas with relatively higher elevation, thereby having higher DTM values. The DSM derivative exhibits similar property as the DTM, which might be eliminated in other DTs because it’s redundant.

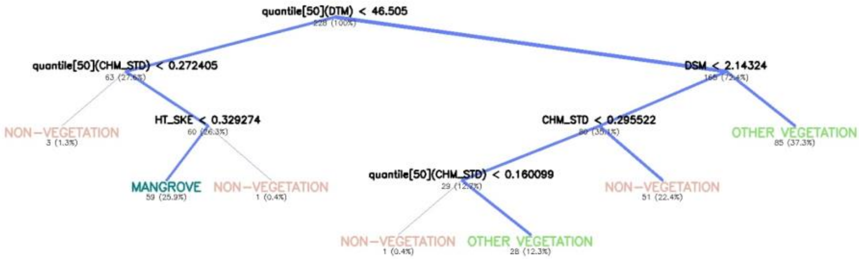


Figure 3. Decision Tree for Calatagan, Batangas.

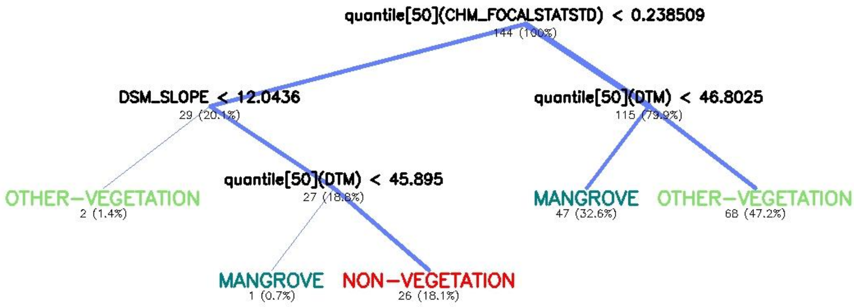


Figure 4. Decision Tree for Lian, Batangas.

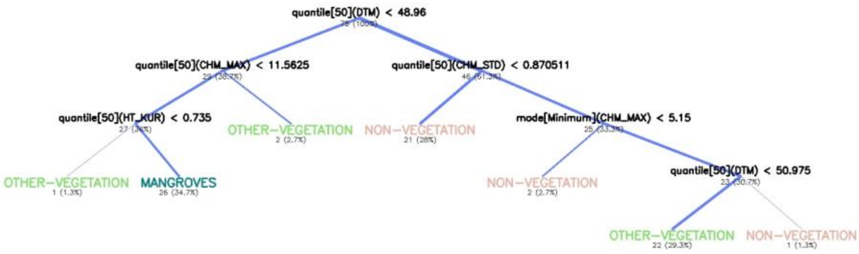
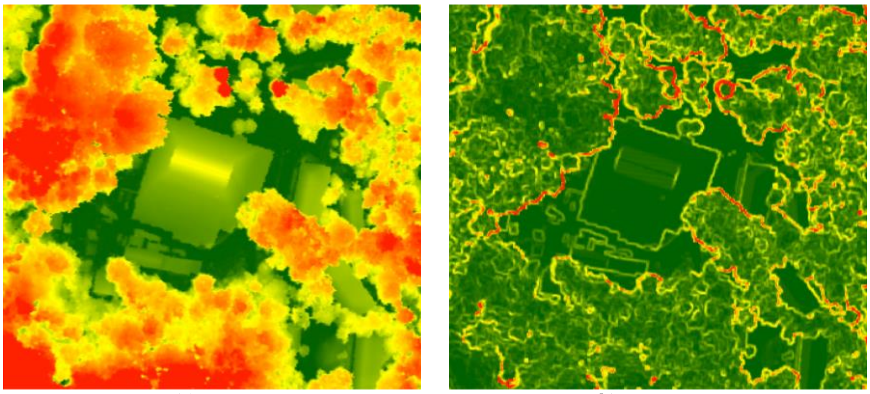


Figure 5. Decision Tree for Infanta, Quezon.

Table 2. Variable importance generated from DTs.

Variable	Importance
Calatagan	
quantile[50](DTM)	0.2822
Standard deviation DSM	0.2154
quantile[50](CHM_STD)	0.1931
Standard deviation CHM_STD	0.1575
Mean HT_SKE	0.1518
Lian	
quantile[50](DTM)	0.5032
quantile[50](CHM_STD)	0.3267
Standard deviation SLOPE	0.1701
Infanta	
quantile[50](DTM)	0.3732
quantile[50](CHM_STD)	0.2237
quantile[50](CHM_MAX)	0.1385
quantile[50](HT_KUR)	0.1378
mode[Minimum](CHM_MAX)	0.1268

Examining the built DTs reveal that CHM_STD has also a strong decisive power. It can be explained by the fact that the said feature is useful in determining other vegetation versus non-vegetation. Other vegetation (i.e., trees) have high values of CHM STD because of the varying heights in an object, while non-vegetation (i.e., buildings) have lower values of height standard deviation. The slope derivative exhibits the same property, as found in DT for Calatagan; however, it might be eliminated from the other DTs because it was found as redundant.



(a) CHM (b) CHM_STD

Figure 6. Comparison of CHM and CHM_STD on vegetation and non-vegetation.

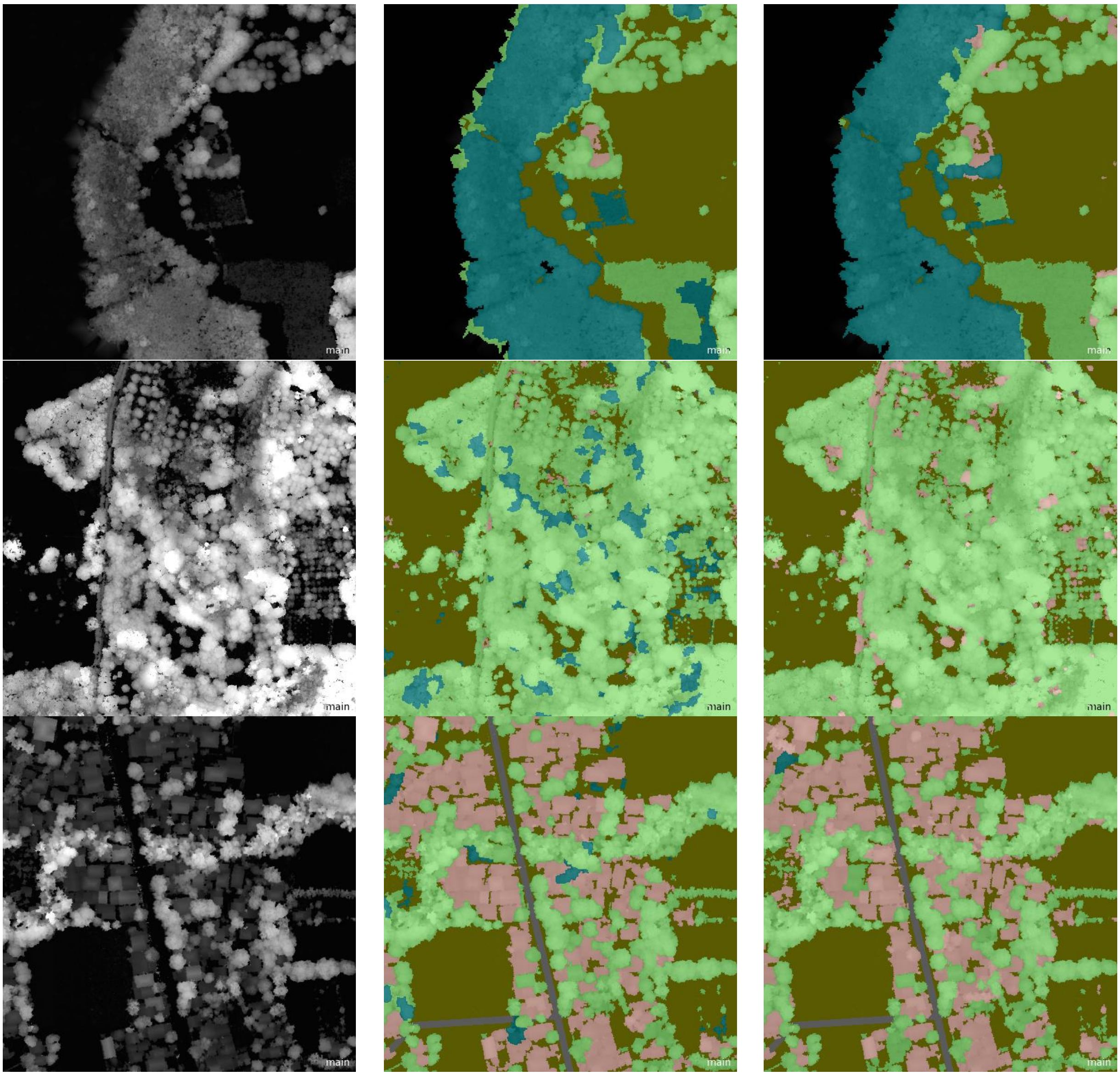
Table 3. Summary of results.

	Processing Time (s)	No. of features used	Overall Accuracy	KIA	Reduction of time	Reduction of features
Calatagan						
SVM_{ALL}	995.75	60	0.8595	0.7634	---	---
SVM_{DT}	75.75	5	0.9477	0.9091	92.39%	91.67%
Lian						
SVM_{ALL}	1974.45	60	0.8399	0.6908	---	---
SVM_{DT}	268.06	3	0.9382	0.8830	86.42%	95.00%
Infanta						
SVM_{ALL}	450.907	60	0.8945	0.8256	---	---
SVM_{DT}	39.00	5	0.8758	0.7967	91.35%	91.67%

One of the goals of this study is to reduce the time of processing when using SVM. It can be obtained by reducing the input layers use when performing SVM. By using DT as a variable selection technique, reduction of processing time when performing SVM was attained since only the important layers were used in the classification. Table 3 shows the comparison of the processing time between SVM using all height metrics and SVM using only the suggested layers by DT. It can be observed that processing time was reduced at an average value of 90%. Moreover, important variables ranged between 3 and 5, out of the 60 available inputs, accounting to 92.78% average reduction of features.

With respect to accuracy, improvement was apparent in Calatagan and Lian as indicated by the increase in both overall accuracy and Kappa Index of Agreement. This is also supported by the visual appeal of the resultant classification. Different settings in the classified image (Fig. 7) depicts improvement, be it in the mangrove area, other vegetation and built-up area. "Scattering" of mangroves can be observed in SVM_{ALL}, which was improved by performing feature selection in SVM_{DT}.

For Infanta, Quezon, a slight decrease was observed in its overall accuracy and KIA after applying SVM_{DT}. This might be attributed to the number of training samples: 75 for Infanta, 144 for Lian and 228 for Calatagan. The said location has the lowest number of training samples. Studies and actual applications suggest that adding more training points can reduce the effect of over-fitting and consequently leads to improvement of the predictor. Recall that the DT is built by recursively examining the learning samples.



(a) CHM (b) SVM_{ALL} (c) SVM_{DT}

Figure 7. Comparison of outputs for SVM classification.

4. CONCLUSION

The method developed in this study proves to be an effective and efficient feature selection technique prior to SVM classification. It exhibits effectiveness in the sense that the classifier produced better generalization as it avoided over-fitting indicated by the increase in overall accuracy and kappa coefficient. Also, DT-based SVM is more efficient as it reduces the number of input for training and classification at an average of 90% reduction; and, it makes the processing time shorter, resulting to an average reduction of 92.78%. For the study area with slightly lower OA and KIA, adding more training samples can lead to better results.

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