Evaluation of Object-Based Classification Methods For Mapping Benthic Habitats Using Bathymetric LiDAR Derivatives

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Abstract — *Benthic habitats are one of the most productive ecosystems in existence. Unfortunately, they are declining in coverage globally due to natural and anthropogenic factors. Mapping and monitoring the status of these coastal ecosystems is critical for their protection. One of the tools capable of mapping such habitats is LiDAR remote sensing. This research aims to evaluate different object-based classification methods for classifying benthic habitats in Manicani Island, Guiuan, Eastern Samar using LiDAR derivatives. The bathymetric LiDAR data used in this research was obtained using an Optech Aquarius ALTM sensor. Before classification, LiDAR derivatives such as digital surface model (DSM), depth, plan curvature, profile curvature, rugosity, slope, slope of slope, broad-scale and fine-scale Bathymetric Position Index (BPI), and fractal dimension were extracted from the raw data. Principal components analysis was applied to eliminate redundant information. To classify the benthic habitats, an object-based image analysis (OBIA) approach was performed using eCognition. Training and validation data sets utilized in classification and accuracy assessment were gathered in the field using a handheld GPS receiver and video tows geotagged using a dual-frequency GPS receiver. The overall accuracies achieved in mapping benthic habitat from LiDAR derivatives were as follows: Hierarchical – 77.4%, Nearest Neighbor – 88.3%, Feature Space Optimization (FSO) – 82.4%, and SEparability and Thresholds (SEaTH) – 81.9%.*

Keywords — benthic habitat mapping, bathymetric LiDAR, OBIA, hierarchical classification, nearest neighbor, FSO, SEaTH

I. INTRODUCTION

Considered as one of the countries with the longest coastlines, the Philippines houses and supports diverse marine ecosystems that provide shore protection, nutrient cycling, and valuable economic goods. It is an archipelagic country with the second most extensive coral reef area in Southeast Asia covering about 25,000 square kilometers [1], [2]. Many of its people depend on coastal resources for daily necessities such as food. Due to population growth and industrialization, the coastal environment and its resources are being threatened. Approximately 70% of the municipalities in the Philippines are in the coastal area accounting for anthropogenic activities and vulnerability to disturbances, natural phenomena, exploitation, and pollution of the coastal zone causing threats to marine biodiversity and coastal resources. Integrated coastal management is widely recognized as the basis for sustainable use and to achieve this, evaluation and mapping of the resources are needed. Inventory of these resources provides important baseline data for resource management which can help in decision making, planning, and development. With this, the development of methods for mapping and establishment of the coastal resources' geographic location and extent is important to aid in the assessment, monitoring, and management of marine ecosystems effectively [3].

Part of these marine ecosystems is the benthic community. They are biological communities thriving on the seafloor which include seagrasses, seaweeds, and corals [4]. Benthic habitats are the bottom substrates which shelter these benthic communities. They support a diversity of marine life by providing shelter, nursery, and food. Coral reefs typically grow in shallow, sunlit waters [5] while seagrasses and seaweeds thrive in intertidal zones [6]. Mapping these coastal habitats is essential in creating coastal resource management plans [7], [8]. Benthic habitat maps can support in creating guidelines for the establishment of marine protected areas and marine spatial planning. Furthermore, it can be used in the status assessment of benthic resources, detection of changes in spatial cover and species abundance, habitat delineation, and offshore engineering [9]. These maps can also provide better insights on ecological patterns and processes across the seabed [7], [8]. To monitor and map benthic habitats, research papers have identified remote sensing as an efficient and effective tool for such purposes [3], [9]–[11].

LiDAR, which stands for Light Detection and Ranging, is an active remote sensing system that operates in the infrared, visible, or ultraviolet wavelengths of the electromagnetic spectrum [12]. Airborne LiDAR for bathymetric and topographic mapping has gone through considerable advancement and improvement since the early 1970s [13]. Through time, the cost of airborne LiDAR mapping systems lessened along with the availability of more compact and lightweight systems which led to the technology being more commercially viable. LiDAR is capable of rapid collection of highly accurate elevation data over a large area for a short amount of time [14]. It emits its own laser pulse and measures distance by determining the time between transmitting and receiving the laser pulse signal [15]. The distance between the sensor and the surface object is calculated by multiplying the return's signal elapsed time by the speed of light and dividing it by two to account for the roundtrip travel it made (Equation 1) [16]. The output of a LiDAR system is not an image but a collection of points called the "point cloud" [17]. Each point contains 3D coordinates of the target object which are calculated from the distance and angle traveled by the laser pulse. There are two general types of imaging LiDAR, topographic and bathymetric. The bathymetric LiDAR systems are designed to penetrate water surfaces. They emit a short green pulse in order to maximize penetration in water for different water types [18]. On the hand, topographic LiDAR systems are mainly utilized for terrestrial mapping applications and they usually emit pulses in the near-infrared range.

$$Distance = \frac{time_L * speed\ of\ light}{2} \tag{1}$$

Equation 1. Distance between sensor and the surface object

The bathymetric LiDAR is a relatively new technology introduced in the Philippines. An extensive LiDAR survey of the country was started in 2011 and approximately two-thirds of the Philippines was surveyed using LiDAR technology. This task was accomplished by utilizing four LiDAR sensors, three of them were topographic LiDAR and one was a bathymetric LiDAR. The data from the bathymetric LiDAR were used in this research to determine its capability for mapping coastal resources such as benthic habitats. The quantitative high-resolution information on coastal elevation derived from LiDAR has vast potential in coastal research and resource management. In the Philippines, where the majority of the population lives in the coastal zone, accurate and updated coastal topographic and resource extent maps and are essential and necessary because they are the basic requirements utilized by policy and decision-makers, planners, managers, and researchers for their respective purposes. Usually, these maps are prepared using data from *in situ* surveys.

Traditional *in situ* surveys are challenging, time-consuming, and labor-intensive. Thus, throughout the years, satellite and airborne remote sensing methods have been optimized in mapping and inventory of shallow benthic habitats. [19], [20]. With LiDAR technology, data and information can be collected rapidly offering high resolution, high accuracy measurements. And over the years, its scientific uses have continued to evolve. Zavalas et. al. (2014) demonstrated the potential of utilizing bathymetric LiDAR for the effective classification of benthic habitats in shallow water (< 30m). A study by Wedding et al. (2008) found that LiDAR provides an effective measure for rugosity on a coral reef in Hawaii. Results suggest that LiDAR-derived rugosity may be used as a surrogate for various fish measures of fish assemblage structure which implies that LiDAR data may be used to assist in prioritizing areas for conservation and management [18]. This was also established by Brock and Purkis (2009) when they reviewed various articles on the role of LiDAR remote sensing in coastal research and resource management. They presented studies on how LiDAR can be utilized to examine the geomorphic structure and change in shallow benthic environments [2]. Moreover, LiDAR data can provide information about the topography, physical structure, and complexity of the seafloor. Some studies utilize this information to analyze the benthic terrain and distribution of benthic habitats. Examples of topographic information which can be derived from LiDAR data are the mean depth, standard deviation of depth, curvature, plan curvature, profile curvature, rugosity, slope, slope of slope, broad-scale and fine-scale bathymetric position index, and fractal dimension [21] Furthermore, according to Collin et. al. (2011) [22], an object-oriented segmentation that considers the spatial context may be better than traditional pixel-based classification in mapping shallow water seabed.

Several studies have compared various classification algorithms in mapping benthic habitats using remote sensing datasets. Hasan et. al. (2012) assessed four supervised learning methods – Maximum Likelihood (MLC), Quick, Unbiased, Efficient Statistical Tree (QUEST), Random Forest (RF) and Support Vector Machine (SVM), in classifying habitat classes using multi-beam echosounder backscatter data [23] while in the study of Wahidin et. al. (2015), object-based classification methods such as SVM, Random Tree, k-Nearest Neighbor, Bayesian and Decision Tree were utilized for mapping using Landsat satellite data [24]. Moreover, Collin et. al. (2011) assessed benthoscape (i.e. benthic habitats and their associated communities) discrimination by object-oriented classification of bathymetric LiDAR. They utilized twelve (12) bottom descriptive statistics such as mean, variance, skewness, kurtosis, etc. and compared an unsupervised classification method, K-means, and supervised classification method, SVM.

Advancement in remote sensing technology, increase in computation capability, and availability of high-resolution imagery prompted the emergence of object-based image analysis (OBIA) [15]. OBIA has been a tool for the classification of benthic features and considered to be more accurate than the pixel-based technique [25], [26]. Classifying various landforms using OBIA of high-resolution imagery has been proven more superior than pixel-based classification [27]–[29]. The approach uses objects as the processing units to classify the image. The objects are created by segmenting the image into regions based on the different criteria for homogeneity [30]. OBIA starts with the generation of segmented objects at multiple levels of scales [27] and builds on edge detection, feature extraction, and classification concepts [31]. This classification method is tested in this research for classifying benthic habitats from LiDAR data.

This relatively new technology may be the key to improving the baseline mapping of coastal resources in the Philippines. Although satellite images have been widely used in the country for benthic habitat mapping, additional information from LiDAR surveys may be proven useful and may provide supplementary data for existing methods. The objective of this research is to evaluate object-based classification methods, specifically, Hierarchical Classification, Nearest Neighbor, Feature Space Optimization (FSO), and SEparability and Thresholds (SEaTH) in mapping benthic habitats from LiDAR derivatives.

II. MATERIALS AND METHODS

A. Study Area

The study area is located in Manicani Island, Guiuan, Eastern Samar, Philippines (Figure 1). This island is found in the Leyte Gulf and is situated at 10.93°N and 125.63 °E. Manicani Island is dominated by corals and seagrasses. Eastern Samar’s coast is covered by fringing coral reef [32] and seagrass meadows.

The benthic habitats in Manicani Island which were included in the classification were corals, dense seagrass, sparse seagrass, seaweeds, sand, coral rubbles, and dead corals (with algae). Corals make up a coral reef and they consist of thousands of individual polyps [33]. They thrive in clear, shallow, and warm water. On the other hand, seagrasses, flourish in the intertidal zone. They are flowering plants that can live entirely submerged in water [6]. Moreover, seaweeds, also known as macroalgae are free-floating plants [34].

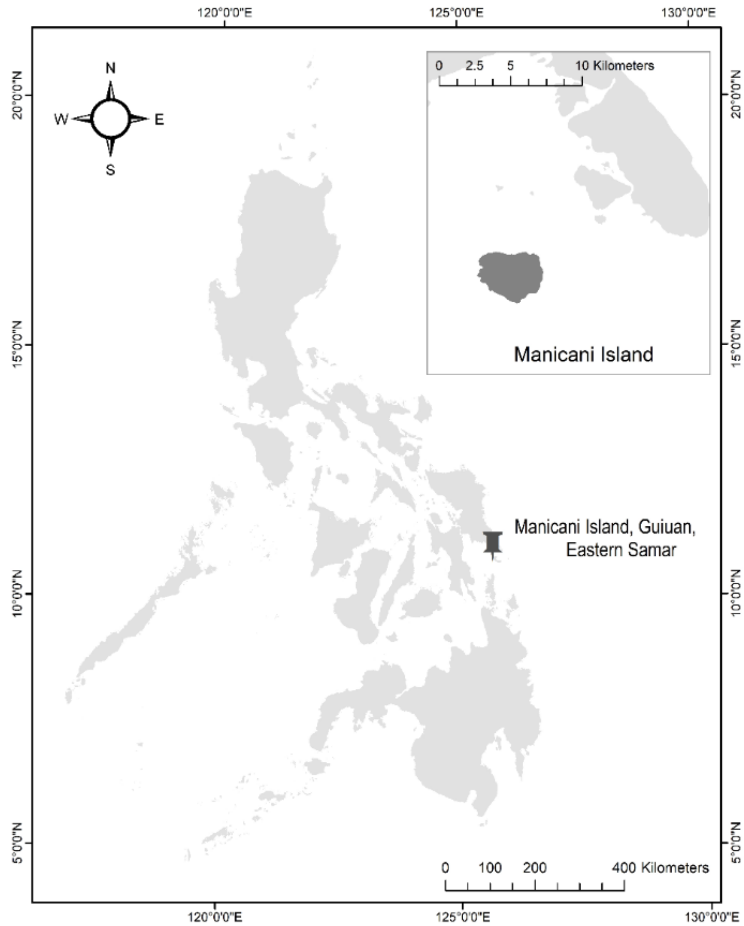

Figure 1. Map showing the location of the study area: Manicani Island, Guiuan, Eastern Samar

B. Data

The LiDAR dataset of Manicani Island (Figure 2) is a missioned flight using an Optech Aquarius ALTM sensor which utilizes green laser (532 nm wavelength). The resolution is two points per square meter and it was preprocessed using the LAStools software.

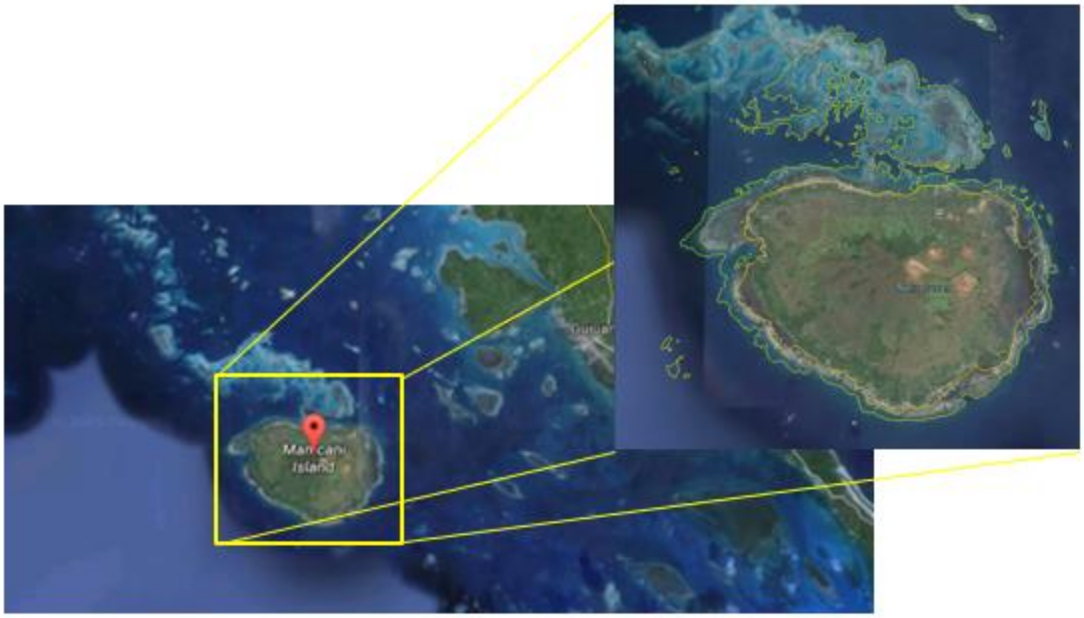

Figure 2. The extent of the extracted bottom of the bathymetric LiDAR data (yellow polygon) in Manicani Island

LAStools is one of the fastest and memory-efficient solutions for batch processing of LiDAR data [35]. It was utilized to separate the surface points from the bottom points. Water depths can be calculated by getting the distance between the sea surface and the bottom. The green laser utilized by the bathymetric LiDAR is partially reflected from the water surface to the bottom as seen in Figure 3. The water surface points were eliminated to create the bottom surface. Other unnecessary points were also cleaned out such as land and noisy data. The digital surface model (DSM), a spatially continuous digital product [15] extracted from the bottom surface discrete points, was created by performing interpolation.

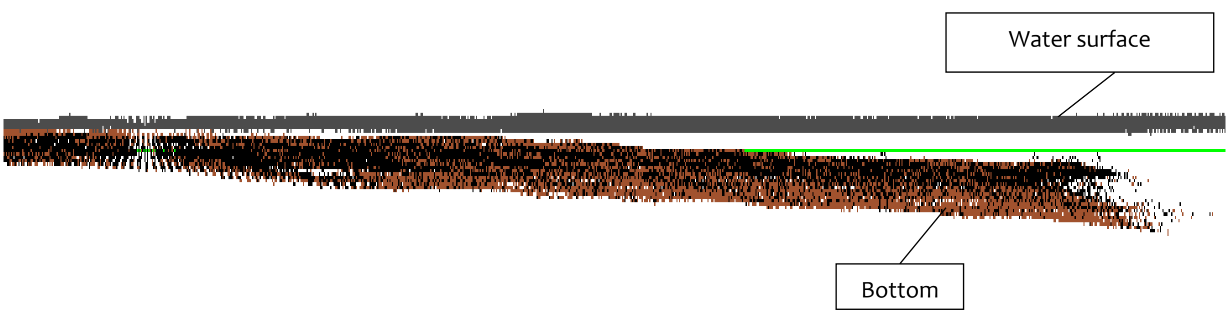

Figure 3. Surface (gray line) and bottom (brown area) bathymetric LiDAR data points where green laser utilized by the bathymetric LiDAR is partially reflected from the water surface to the bottom.

The digital surface model (DSM) of the water bottom provides valuable information in producing benthic habitat maps. Aside from depth information, it can also be utilized to extract information about the seafloor's topography and physical structure [21]. Moreover, different terrain variables can be derived from the DSM such as mean depth, standard deviation, curvature, plan curvature, profile curvature, slope, slope of slope, rugosity, broad-scale and fine-scale Bathymetric Position Index (BPI), and fractal dimension. The mean depth and standard deviation of the depth are depth summary statistics which are useful predictors in understanding the benthic zones, particularly in habitat classification. The mean depth is the average water depth while the standard deviation of depth describes the amount of dispersion of water depth values about the mean [21]. Aside from depth summary statistics, bottom terrain parameters can also be derived from the DSM.

Terrain parameters such as curvature, slope, rugosity, broad-scale and fine-scale BPI, and fractal dimension can provide information to characterize the seabed. They are valuable information to define areas of continental slope that are highly probable for supporting certain fauna and thus provide a distinct habitat [36]. Curvature is the rate of change in curvature across the surface which highlights ridges, crests, and valleys. Moreover, plan curvature is the curvature of the surface perpendicular to the slope direction, while profile curvature is the curvature of the surface in the direction of the slope. In curvature and plan curvature, negative values denote concave and positive values are convex surfaces. However, for profile curvature, negative values are convex and positive values are concave [21]. Slope, on the other hand, is a measure of steepness while the slope of slope is a second derivative of the bathymetric height. It can capture fine-scale topographic complexity for predicting both fish and coral metrics [37]. Rugosity is a measure of surface roughness and is described as the ratio of surface area to planar area [21]. It can be used as a predictor of fish species richness and abundance, as well as seagrass distribution in different bottom type variations. It can also be a way to distinguish coral-dominated habitats. Slope and rugosity are considered as potential proxies for benthic biodiversity by defining the structures on the seafloor [38]. BPI is a measure of the relationship of a certain location with a defined elevation in relation to the overall landscape. Positive (negative) values represent cells that are higher (lower) than the neighboring cells, whereas near-zero values depict flat areas or areas with a constant slope. Broad-scale BPI analyzes a larger neighborhood while the fine-scale BPI detects smaller and localized terrain variations. Lastly, the fractal dimension indicates how the surface roughness changes over space. Values range between 2 for smooth and 3 for rough surfaces [39]. All of these datasets were derived from the DSM.

Since the derivatives all originated from the DSM, there was a high possibility of redundant information in each of these surfaces. Thus, to reduce the likelihood of redundancy, the derivatives were stacked together and Principal Components Analysis (PCA) was applied. This procedure transforms the highly correlated bands into uncorrelated output bands. PCA transformation is a multivariate statistical technique that chooses uncorrelated linear combinations of variables to generate principal components (PC) which has a smaller variance [40]. The number of bands produced by PCA is similar to the number of input bands, subject to selection based on the eigenvalue.

C. Data Processing

The capability of mapping benthic habitats using LiDAR data was analyzed using the bathymetric LiDAR flight of Manicani Island. After cleaning the data, eleven (11) LiDAR derivatives such as mean depth, standard deviation, curvature, plan curvature, profile curvature, slope, slope of slope, rugosity, broad-scale BPI, fine-scale BPI, and fractal dimension were produced using LandSerf and the Benthic Terrain Modeler in ArcGIS 10 (Figure 4). PCA was then applied to remove the redundancy of information.

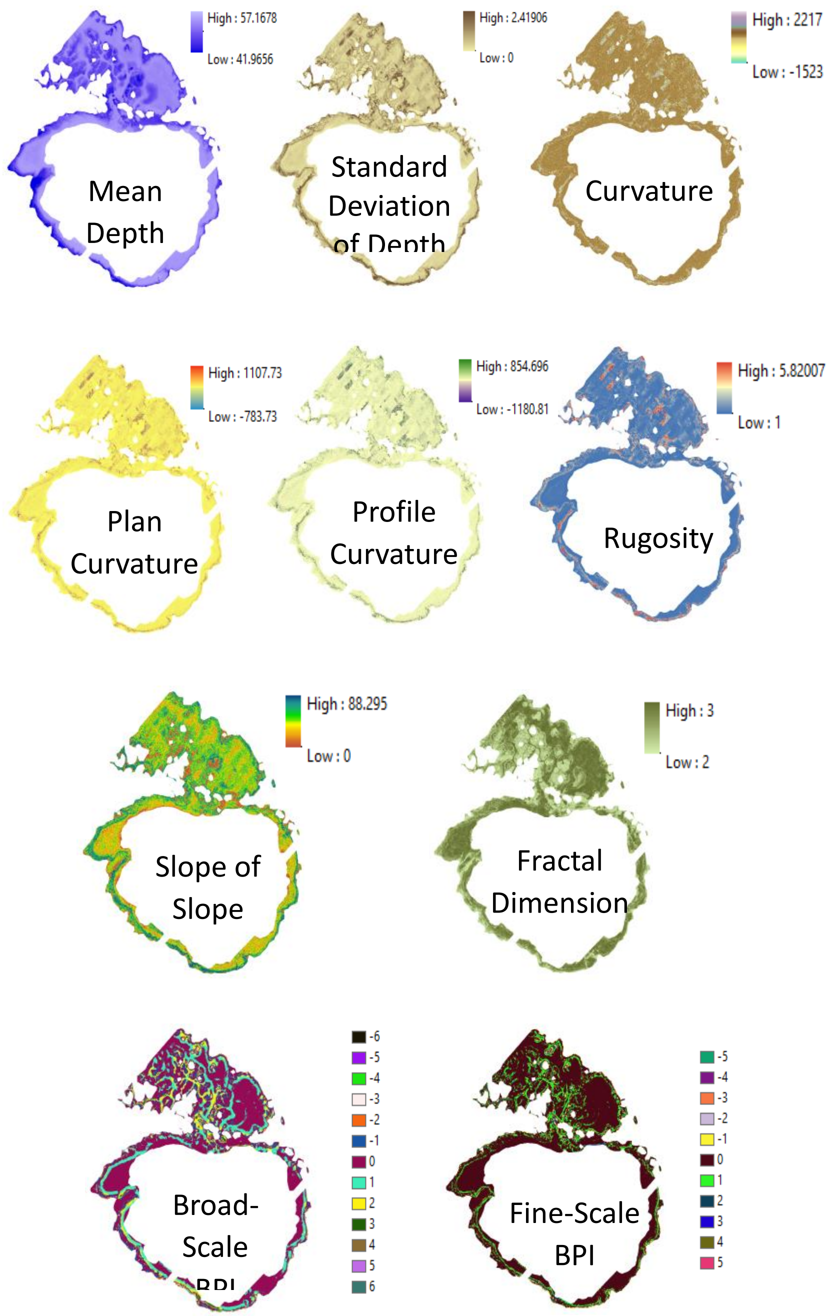

Figure 4. Derivatives of the bathymetric LiDAR data of Manicani Island

The PCA raster and the LiDAR derivatives were imported to the eCognition software, which was used to perform OBIA. To delineate the different benthic habitats in the data, multiresolution image segmentation was employed. One of the first steps in every remote sensing image analysis is the image segmentation [41], [42]. It is a basic and critical task in image processing as it effectively partitions an image into different meaningful regions or objects [41], [42].Each region is homogeneous in some sense, e.g. parts of the region have the same brightness, color, or texture. The eCognition software creates the segments based on three parameters: scale, shape, and compactness. The segmentation commences by initially recognizing each individual pixel in the image as one segment. These single-pixel segments are then successfully merged into larger segments using pair-wise clustering processes [43]. Several combinations of these criteria can be made to obtain different results. Scale dictates the relative size of the regions while shape and compactness determine the smoothness and optimizes the regions' spatial complexity. As an example, a small-scale value of 10 produces small segments while a large-scale value of 100 produces large segments. A low shape value of 0.1 places high emphasis on color which is normally the most important factor for creating meaningful objects [43]. Higher compactness weightings of 0.9 result in more compact object boundaries, typical for crop field or building extraction. The best segmentation for each set of data was selected using a trial-and-error approach. It was determined based on the resulting habitat delineation's closeness to field data and image interpretation findings. The final parameters chosen were as follows: scale parameter of 5, shape of 0.2, and compactness of 0.9. A sample area of the result of the multiresolution image segmentation is shown in Figure 5.

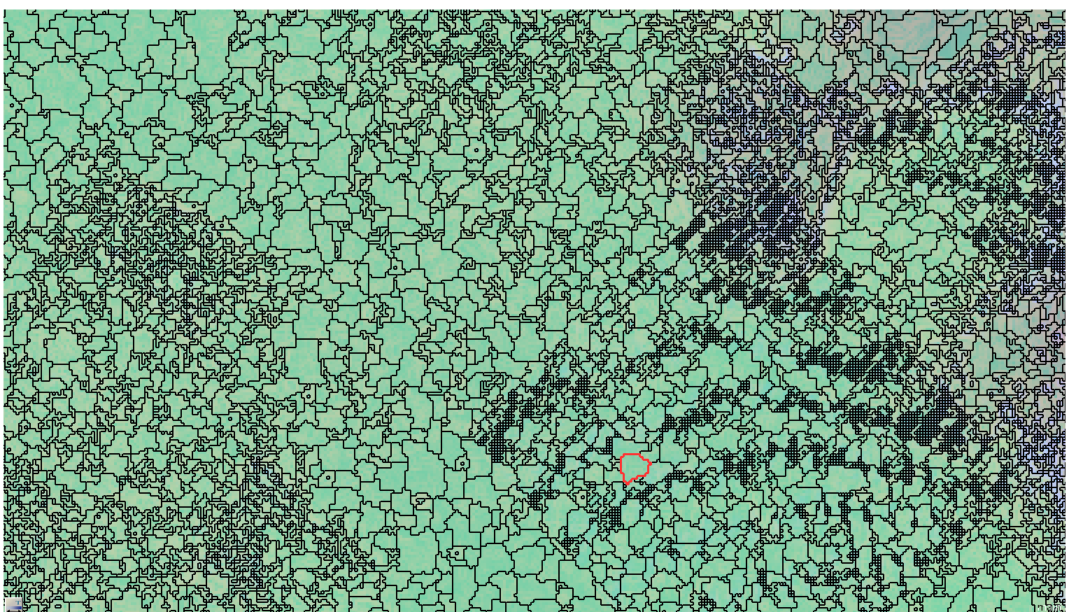

Figure 5. Results of the multi-resolution segmentation showing different regions

After segmentation, the benthic habitats were classified. Different object-based classification methods were performed such as Hierarchical Classification, Nearest Neighbor, Feature Space Optimization (FSO), and Separability and Thresholds (SEaTH). Hierarchical Classification is a rule-based classification method and two important features are needed for this kind of classification. The first is the attribute to be used to create the most efficient split, and the second is the threshold at which to split the attribute. For the first level, benthic habitats were split into shallow and deep regions. Depth is a crucial parameter in the split between shallow and deep regions. This is because depth determines the amount of light reaching the sea bottom and benthic habitats need light to survive. Only corals are most likely to survive in deeper waters. For the second level, the shallow region was then further classified into sparse seagrass, dense seagrass, seaweed, and corals. Textural information such as fractal dimension was determined useful in splitting the classes at this level. The last split includes separating the coral class into coral, sand and dead coral.

Figure ***6*** shows the levels of the hierarchical splits. Aside from Hierarchical Classification, semi-automated object-based classification methods such as Nearest Neighbor, FSO, and SEaTH were also implemented.

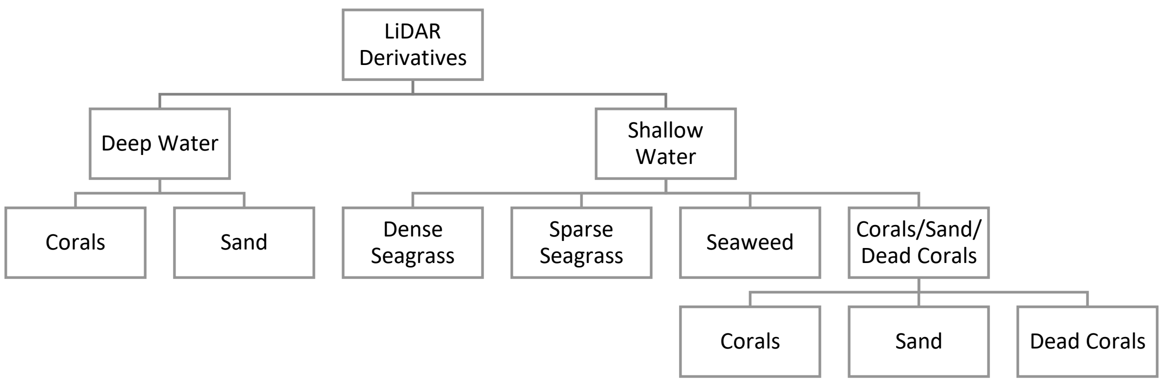

Figure 6. Levels of the Hierarchical Classification of Benthic Habitats from LiDAR Derivatives

Nearest Neighbor classification in eCognition is a supervised classification algorithm that searches for the closest sample image object in the feature space of an object to be classified. The process consists of using training data as samples to teach the algorithm and classifying image objects based on the nearest sample neighbors [44]. The mean and standard deviation of the input image layers were used for the training and classification. On the other hand, Feature Space Optimization (FSO) function is used in conjunction with the nearest neighbor classifier, which performs a mathematical computation in order to determine the best combination of features that will be used for separating classes [43]. Moreover, a feature analyzing tool called Separability and Thresholds (SEaTH) was also used to determine a separate combination of features. SEaTH identifies the pairwise separability of the classes among each other and then determines the thresholds that define the maximum separability of the features [45]. To assess the accuracy of the classification, error matrices were produced based on field survey data.

An error matrix is a means of quantifying the performance of a classification [46]. It is a square matrix (**E**) which consists of *N x N* elements, where N is the number of classes in the classified image. The number of pixels known to belong to class *i*, placed in row *i* and the classified as belonging to class *j*, placed in column *j*, is the element $\mathbf{E}ij$ [47]. The user's accuracy (shown in Equation 2), also called consumer's accuracy, is examined from the user's perspective [48] and it is calculated by dividing the number of correctly classified pixels in each category by the total number of pixels that were classified in that category [49]. On the other hand, the producer's accuracy (shown in Equation 3) is examined from the analyst's point of view [48] and it is computed by dividing the number of correctly classified pixels in each category by the number of test pixels used for that category [49].

$$\frac{\boldsymbol{E}_{ii}}{\sum_{j=1}^{N} \boldsymbol{E}_{ji}} \tag{2}$$

Equation 2. User's Accuracy

$$\frac{\boldsymbol{E}_{ii}}{\sum_{j=1}^{N} \boldsymbol{E}_{ij}} \tag{3}$$

Equation 3. Producer's Accuracy

From the error matrix, the overall accuracy, shown in Equation 4, can also be calculated. The overall accuracy is the simplest and most widely used accuracy measure in remote sensing and it is computed by dividing the total number of correctly classified pixels by the total number of reference pixels [49]. In this research, the error matrices were calculated using data gathered in the field.

$$\frac{\sum_{i=1}^{N} \boldsymbol{E}_{ii}}{\sum_{i=1}^{N} \sum_{j=1}^{N} \boldsymbol{E}_{ij}} \tag{4}$$

Equation 4. Overall Accuracy

During the field survey, GPS data, photos, and video clips of the benthic features found on the seabed were collected. Samples include sparse and dense seagrass, seaweed, sand, dead coral with algae, corals, and coral rubble. The total points were divided into training and validation points which were used for classification and accuracy assessment, respectively. A summary of the workflow performed to classify benthic habitats from LiDAR derivatives is shown in Figure *7*.

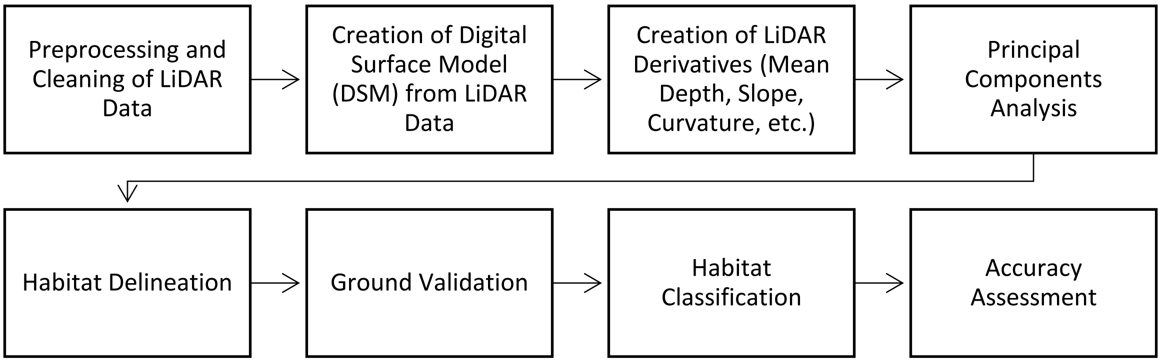

Figure 7. Workflow for extracting benthic habitats from LiDAR data

III. RESULTS AND DISCUSSION

Through the years, airborne laser scanning systems such as LiDAR are evolving and have been opening additional possibilities for surveying the coastal ecosystem. Such systems produce data that can be characterized as sub-randomly distributed 3D point clouds. The first step in processing laser scanner data is removing unwanted measurements [50]. In the case of bathymetric LiDAR for benthic habitat mapping, these unwanted measurements include the water surface, marine organisms, and floating objects. Eliminating erroneous points from the data is crucial in generating correct LiDAR derivatives. Aside from cleaning the data, checking the quality of the acquired points is also highly recommended. This may include inspection of the correctness of the elevation and positional information of the LiDAR points. These steps are included in the preprocessing stage of the LiDAR data to prepare it for classification.

After preprocessing, the LiDAR derivates such as DSM, mean depth, standard deviation, curvature, plan curvature, profile curvature, slope, slope of slope, rugosity, broad-scale and fine-scale BPI, and fractal dimension were produced. Depth statistics are advantageous parameters in separating the benthic habitats because generally, coastal ecosystems have natural zonations [51], [52]. For example, seagrasses are known to commonly thrive in the intertidal zone where the waters are shallower compared to where corals live. Corals act as wave buffers for seagrasses because the latter is susceptible to uprooting due to strong currents. Texture information such as rugosity is also beneficial in separating the classes because it depends on the complexity of the surfaces. Seagrasses, corals, sand, and seaweed have distinct textural surfaces which helps separating them into classes. Even though LiDAR data lacks in spectral information, LiDAR derivatives can be extracted and utilized to map different benthic habitats.

To assess the potential of bathymetric LiDAR for benthic habitat mapping, different object-based classification methods such as Hierarchical classification, Nearest Neighbor, FSO, and SEaTH were applied to the LiDAR data of Manicani Island and the results were assessed for their accuracy. It was classified into seven classes: corals, coral rubble, dead coral with algae (DCA), dense seagrass, sand, seaweed, and sparse seagrass. The result of the classification is shown in Figure 8. Overall accuracies ranging from 77-83% were achieved in classifying the stacked image of LiDAR derivates which shows the potential of bathymetric LiDAR for mapping benthic habitats.

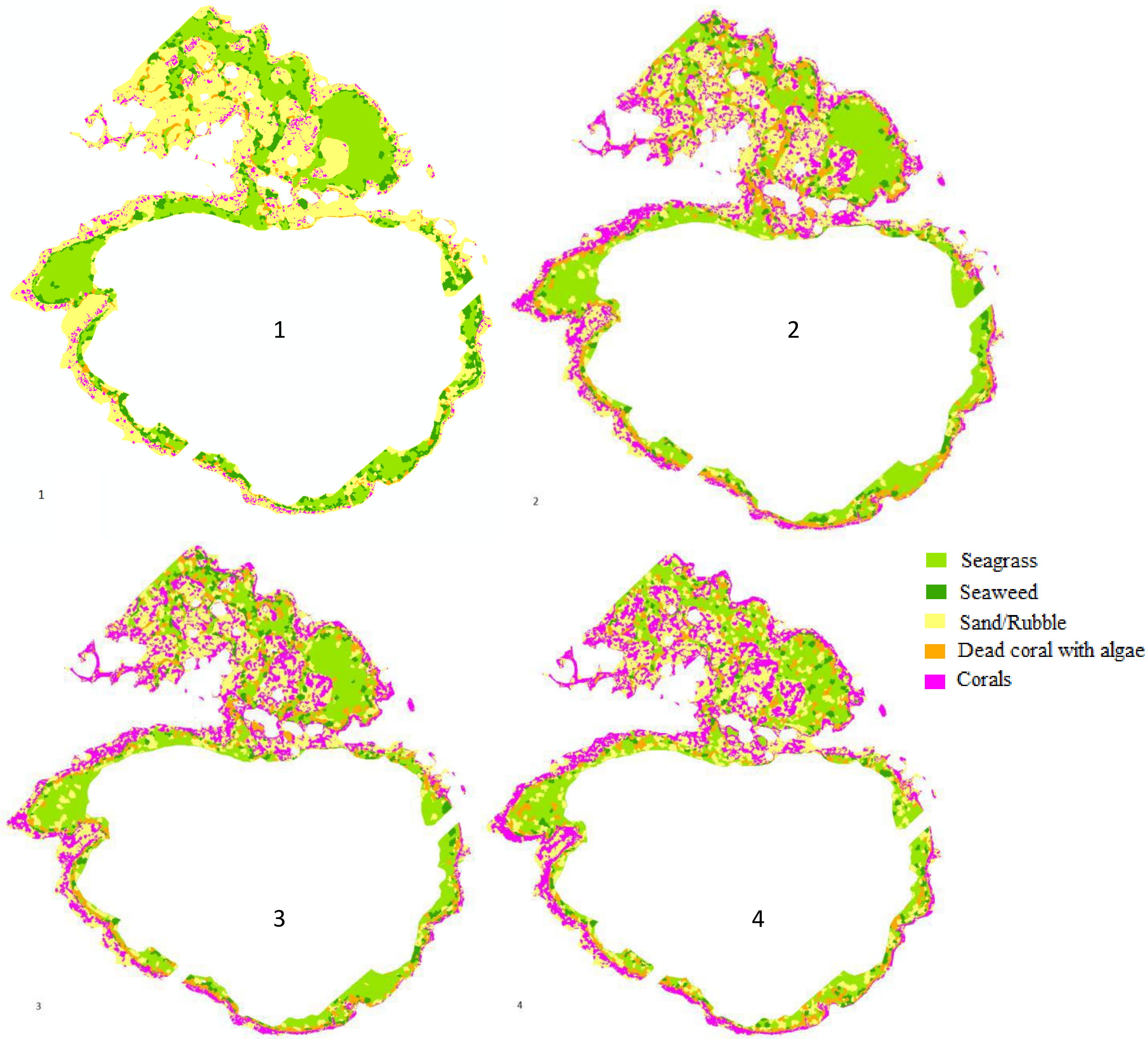

Figure 8. The classification results of the Manicani Island LiDAR data using (1) Hierarchical – 77.4%, (2) Nearest Neighbor – 88.3%, (3) Feature Space Optimization – 82.4%, and (4) SEparability and Thresholds – 81.9%

In the Hierarchical Classification approach, the first PCA band and fractal dimension were the two attributes used to split the different classes. This method produced an overall accuracy of 77.4%. Meanwhile, using Nearest Neighbor, all layers were included in the nearest neighbor feature space which attained an overall accuracy of 83.3%. For the FSO, a total of 30 layers, including the mean and standard deviation of the derivatives, were selected which obtained the best separation distance of 0.364 resulting to a feature combination consisting of the mean of the second band of the PCA raster, the standard deviation of DSM, BBPI, FBPI, and slope. The overall accuracy obtained using FSO was 82.4%. Moreover, using the SEparability and THresholds (SEaTH) tool, the following features were identified to be useful in classifying the benthic habitats: BBPI, curvature, DSM, fractal dimension, depth, the first three PCA bands, plan curvature, profile curvature, and rugosity. These features were then selected in the standard nearest neighbor feature space and applied to the classes. An overall accuracy of 81.9% was obtained in this technique. From the four classifications, corals class was delineated best with producer’s accuracies ranging from 78-94% and user’s accuracies from 93-100% (Table 1). The producer’s accuracy shows the correctly classified objects based on the ground truth information. The resulting producer’s accuracies explain that 78-94% of the validation data for corals are labeled correctly as corals on the benthic habitat map. On the other hand, the user’s accuracy represents the classification from the perspective of the map user. The resulting user’s accuracies explain that 93-100% of the corals depicted on the map actually represent corals on the ground. The class that was mostly misclassified is seaweed, which was misclassified as DCA or seagrass. Among the four, Nearest Neighbor achieved the best overall accuracy with 83.3%.

Table 1. Producer's, User's, and Overall Accuracy Results of Hierarchical Classification, Nearest Neighbor, FSO, and SEaTH.

		Hierarchical Classification	Nearest Neighbor	FSO	SEaTH
Producer's Accuracy	Dense Seagrass	63.50	81.33	78.22	76.89
	Sand	93.10	90.47	92.82	92.82
	Corals	78.64	92.14	86.38	94.10
	Coral Rubble	92.22	75.29	81.98	84.73
	Dead Corals with Algae	65.12	86.24	84.59	79.20
	Sparse Seagrass	88.44	85.70	83.63	86.53
	Seaweed	64.50	70.17	75.35	64.05
User's Accuracy	Dense Seagrass	91.56	85.90	95.70	95.89
	Sand	81.73	74.22	61.77	72.64
	Corals	100.00	93.61	98.81	96.64
	Coral Rubble	50.50	53.58	58.28	52.90
	Dead Corals with Algae	82.24	79.50	71.20	62.50
	Sparse Seagrass	79.98	88.37	93.98	93.00
	Seaweed	56.26	89.67	69.90	71.95
Overall Accuracy		77.44	83.32	82.40	81.95

LiDAR classification highly depends on the textural information of the habitat. Low accuracies due to misclassification are mainly caused by the similarity in the texture of some classes such as sparse and dense seagrass, corals and dead corals, sand, and coral rubbles. Among the lowest user’s and producer’s accuracy is the seaweed class. This is because seaweeds thrive in the habitats of both seagrasses and corals. They are usually seen floating on top of seagrass meadows and coral reefs. Seaweeds also look like seagrasses which may have caused misclassifications. The lowest user's accuracy for all the four classification methods is the coral rubble class. Coral rubbles are easily misclassified as sand if they are small fragments while they may also be mistaken as corals if they are stacked together.

IV. CONCLUSIONS

This study shows that object-based classification of bathymetric LiDAR derivatives can be utilized in extracting the benthic habitats. These derivatives are DSM, depth, standard deviation, curvature, plan curvature, profile curvature, slope, slope of slope, rugosity, broad-scale and fine-scale BPI index, and fractal dimension. They were proven useful in the analysis of the seafloor and identifying the habitats present. An object-based image classification approach has been advantageous in mapping benthic habitats using bathymetric LiDAR as shown in the results. Classifying the Manicani Island bathymetric LiDAR data, overall accuracies achieved were as 77.4%, 88.3%, 82.4%, and 81.9% for the Hierarchical Classification, Nearest Neighbor, and SEaTH, respectively.

It is recommended to apply the methodology in other sites in the Philippines with a larger study area and examine the accuracy of the results in different coastal environments. Moreover, the resolution of the LiDAR data used in this study is two points per square meter. It would be interesting to investigate in future studies the accuracy of classification if the number of points per square meter is increased or decreased. Furthermore, the classification techniques not applied in this research may also be tested in future studies to determine the best classification method for benthic habitat mapping using bathymetric LiDAR.

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