MAPPING FRESHWATER AQUACULTURE FROM LIDAR INTENSITY IMAGE USING OBJECT-BASED IMAGE ANALYSIS

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KEY WORDS: Aquaculture, LiDAR intensity, Canny's edge detection, Sobel filter

ABSTRACT: Previous studies demonstrated the use of satellite images, such as satellite imaging radar, Landsat Thematic Mapper and WorldView-2, in order to map coastal aquaculture. With the advent of LiDAR technology in the Philippines, methods have been developed to extract fish ponds, fish corrals and fish cages using height information (DSM and DTM) and RGB-derived layers from orthophoto taken during the flight mission. In this study, the effectiveness of uncalibrated LiDAR intensity in mapping freshwater culture structures found in two lakes of Quezon province, Philippines was explored. Moreover, two edge detection algorithms were used and compared for fish cage extraction: Canny's method and Sobel filter. Using object-based image analysis and applying rule-based classification, the aquaculture extraction was met, enabling the detection of the fish cages together with the cottages or built-up used by fishermen in the lake. The output map can then be used as a baseline information in managing aquaculture areas specially that these anthropogenic activities have caused devastating fish kills in the Philippines.

1. INTRODUCTION

With the advent of Light Detection and Ranging (LiDAR) technology in the Philippines, detailed and accurate flood hazard maps have been generated. An offspring of the program is Phil-LiDAR 2 which aims to use the LiDAR datasets in order to extract various natural resources including agricultural, coastal, hydrological, forest and renewable energy (Blanco, Tamondong, Perez, Ang, & Paringit, 2015).

This paper focuses on the objective of mapping inland aquaculture structures, as well as estimating the area of production in the study site. The inventory and monitoring of freshwater aquaculture production is an important tool for management agencies, especially in the formulation of regulatory policies, environmental safety and revenue collection. Fish kills in Taal Lake, Batangas were recorded in 2008 and 2011, where 50 metric tons of tilapia and 375 metric tons of milkfish were killed, respectively (InterAksyon.com, 2011). Aside from climate change and other environmental effects, officials said that the fish kill could be caused by "overloading" or the increase of aquaculture production, resulting to too much biomass that spreads the supply of oxygen too thin.

1.1 Aquaculture Production

The Food and Agriculture Organization of the United Nations recognizes the need to have reliable information on matters leading to responsible management of aquaculture. FAO defines aquaculture as "the farming of aquatic organisms, including fish, mollusks, crustaceans and aquatic plants; and that farming implies some form of intervention in the rearing process to enhance production, such as regular stocking, feeding, protection from predators, etc. (Food and Agriculture Organization, n.d.)"

Statistics based on the 2014 Philippine Fishery Resources by the Bureau of Fisheries and Aquatic Resources indicates that 200,000 hectares of aquaculture production can be found on lakes (Bureau of Fisheries and Aquatic Resources, n.d.). In the same year, Region IV-A (covering the provinces of Cavite, Laguna, Batangas, Rizal and Quezon) marked the highest production on freshwater: 76,339.72 metric tons from fish cages and 47,095.70 metric tons from fish pens (Bureau of Fisheries and Aquatic Resources, n.d.).

The Philippine Fisheries Code of 1998 defines a fish cage as an enclosure which is either stationary or floating made up of nets or screens sewn or fastened together and installed in the water with opening at the surface or covered and held in a place by wooden/bamboo posts or various types of anchors and floats. Fish pen is defined as an artificial enclosure constructed within a body of water for culturing fish and fishery/aquatic resources made up of poles closely arranged in an enclosure with wooden materials, screen or nylon netting to prevent escape of fish (Bureau of Fisheries and Aquatic Resources, n.d.).

1.2 Previous Works on Aquaculture Mapping

Motivated by the pioneering work of inland shrimp farm mapping in Sri Lanka using Synthetic Aperture Radar, Travaglia, et al. (2004) mapped coastal aquaculture and fisheries structures in Lingayen Gulf, Philippines using satellite imaging radar. Using remote sensing and GIS methods on ERS-2 SAR image (12.5-m spatial resolution) and RADARSAT-1 SAR image (6.25-m spatial resolution), they were able to obtain accuracies of 100% for fish pens, 95% for fish ponds, 90% for fish cages and 70% for fish traps.

In recent studies, object-based image analysis (OBIA) has been incorporated in mapping coastal aquacultures (Zhang, et al., 2010; Peralta, et al, 2015; Cabanlit, et al., 2015). In OBIA, segmentation is of particularly interest since the goal is to have an output of semantically significant group of pixels. Using a Landsat TM imagery, the study by Zhang, et al. (2010) suggests that OBIA is superior to pixel-based approach in a moderate-scale aquaculture mapping (spatial resolution can be between 15-30 meters). Multi-scale segmentation/object relationship modelling (MSS/ORM) for OBIA is the best strategy to extract aquaculture in processing aerial imagery (Zhang, Li, Yang, Zhou, & Su, 2010) as pixels were grouped based on similar spectral areas and linked spectral properties to information classes.

On the other hand, the work by Peralta, et al. (2015) used LiDAR data and high resolution satellite image from WorldView-2 to extract coastal fish ponds. They demonstrated the effectiveness of Canny's edge detection algorithm in order to segment the aquaculture structures. From the satellite image, the NIR band was used, while the Digital Surface Model (DSM) generated from LiDAR served as input for edge detection in the other set-up. A rule-based hierarchical approach using multi-threshold segmentation algorithm was used. In another setting, fish traps were extracted with 100% accuracy using LiDAR derivatives from the Principal Components Analysis on DSM, slope of slope and rugosity (Cabanlit, Silapan, Pada, Campomanes, & Garcia, 2015).

2. METHODOLOGY

2.1 Study Area and Materials

The study site covers the aquaculture structures found in Tikub Lake (13° 57' 46.00" N, 121° 18' 22.18" E) located in Tiaong, Quezon and Gunao Lake (14° 0' 4.72" N, 121° 22' 16.74" E) found in Dolores, Quezon. Based on the delineated water body from LiDAR data, Tikub Lake has an area of 45.91 hectares (0.46 km^2) and Gunao Lake measures 23.41 hectares (0.23 km^2).

In a recent freshwater survey conducted by Labatos & Briones (2014), a total of 221 individuals comprising nine species from seven families were found in Tikub Lake, three of which are native and six are introduced. They also noted that a native, *Giuris margaritacea* and an introduced, *Poecilia sphenops* are the two most abundant species in the lake, amounting to a relative abundance of 29.41% and 26.24%, in that order. At the time of the study, no literature on fauna survey is available for Gunao Lake.

The LiDAR data was sourced from the Disaster Risk and Exposure Assessment for Mitigation (DREAM^{TM}). Two LiDAR blocks covering the two lakes, VWs and W, were flown in 2014. From the LiDAR point clouds, the normalized Digital Surface Model (nDSM) and maximum intensity (MAX INT) were derived using LAStools.

In this application, intensity image was of interest. LiDAR intensity is a measure of the power backscattered from the target object, which is recorded per point cloud. Because water absorbs LiDAR signal, the return strength of the pulse is lower compared when the signal hits another target, e.g., the fish cage structure usually made of bamboo poles. As a result, the intensity image derived from the LiDAR point clouds outlines the aquaculture structures (Fig. 1).

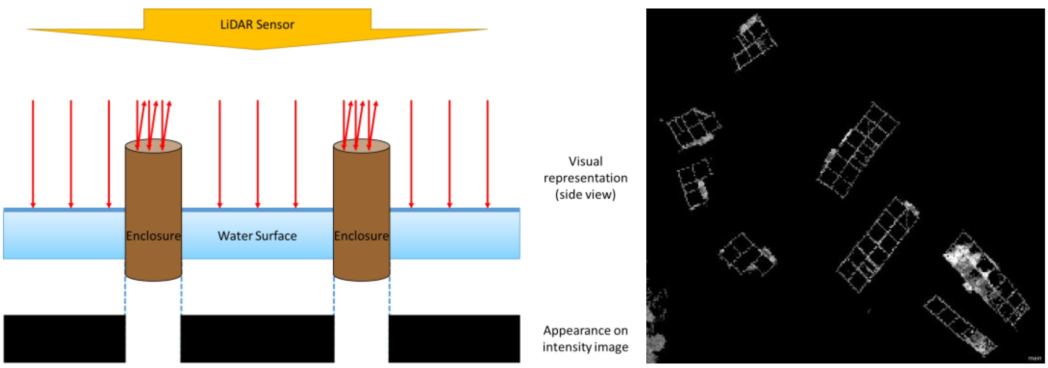


Figure 1. LiDAR intensity image of water and aquaculture structures.

2.2 Edge Detection

Canny's algorithm (1986) in detecting edges and edge information can be found in a wide range of applications, from biomedical image processing, such as in MRI brain edge detection (Laishram, Kumar, Gupta, & Prakash, 2014) and in automatic Tuberculosis screening (Ramya & Srinivasa Babu, 2015), to image reconstruction (Dong, Li, & Li, 2013), facial expression recognition (Shah & Kaushik, 2015), and farmland information extraction (Wang, Fu, & Wang, 2015).

Recently, Canny's edge detection has been proven efficient in feature extraction, outperforming traditional edge detection methods. (Shah & Kaushik, 2015) (Wang, Fu, & Wang, 2015) Implementation through hardware, though complex (Abdullah-Al-Nahid, Kong, & Hasan, 2015), is now available, such as in (Jeyakumar, Prakash, Sivanantham, & Sivasankaran, 2015).

Canny algorithm is a gradient based edge detection (Shah & Kaushik, 2015) method proposed by John Canny in 1986, which was "based on the specification of detection and localization criteria in mathematical form." (Canny, 1986) It starts with the assumption that the image contains (1) the step edge and (2) the additive white Gaussian noise. The process of detection is illustrated in Figure 2, presented by (Abdullah-Al-Nahid, Kong, & Hasan, 2015).

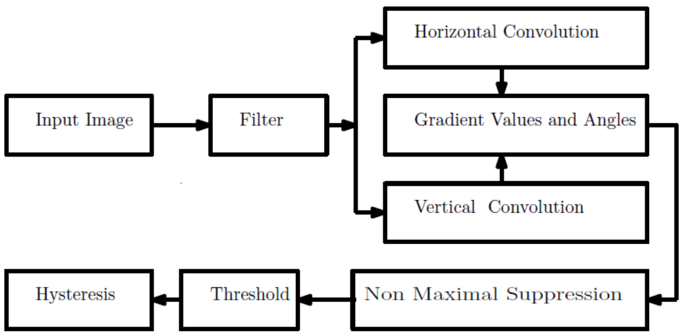


Fig. 2. Block diagram of Canny's edge detection as illustrated by Abdullah-Al-Nahid, et al. (2015).

As further detailed by Canny, detection starts in locating the step edge surrounded by Gaussian noise, which is then convolved with a filter. Using the output of the convolution operation, the goal is to find the filter that "gives the best performance with respect to the criteria" set by Canny. Canny summarized three performance criteria in (Canny, 1986), such as (1) good detection, (2) good localization and (3) only one response to a single edge.

Researches that use Canny's algorithm have modified the traditional Canny edge detection method due to some of the demerits inherent in the method. For instance, application of Gaussian filter in image smoothing can cause losing of weak but significant edge information because of the sensitivity of the Canny algorithm to noise (Zhao, Liu, & Wan, 2015) (Rong, Li, Zhang, & Sun, 2014). Another problem encountered is the fixed value used in the double thresholding, which causes "local characteristic edge information" to be lost easily (Rong, Li, Zhang, & Sun, 2014). The double thresholding technique also makes the traditional Canny edge detector inefficient in dealing with color images. (Sidhu, 2014) Traditional Canny edge detection algorithm is non-adaptive (Dong, Li, & Li, 2013).

Improvements are made depending on the particular application. An improvement has been proposed in (Wang & Fan, 2009) by replacing the Gaussian filter by a self-adaptive filter, and by adopting morphological thinning. Directional filters increases the accuracy of locating edges particularly for the anisotropy features (Huang, Wang, & Li, 2007).

Most researches that use Canny's algorithm are modifying the traditional edge detection approach by introducing complementary methods (Dong, Li, & Li, 2013; Zhao, Liu, & Wan, 2015; Xin, Ke, & Xiaoguang, 2012) depending on the particular application.

Another edge detection applied in the study applied the Sobel filter. Sobel operator filter, or more appropriately named as Sobel-Feldman operator, was developed in 1968 documenting the simple, computationally efficient, gradient operator (Sobel, 2015). Applying the algorithm, edges are found by using the Sobel approximation to the derivative. It shows the edges at points where the gradient of the input layer (grayscale image) is maximum. Default settings in eCognition were applied in both edge detection algorithms.

2.3 Object-based image analysis

Because of the high resolution LiDAR-derived raster layers (1-m spatial resolution), object-based image analysis was used in this study. Fig. 3 below illustrates the rule-based approach developed in this study.

Before proceeding with the actual classification, Canny's edge detection algorithm and Sobel operator filter were applied to intensity layer, generating two layers showing the edges. With the aid of height information from the nDSM, ground and non-ground objects were segmented using multi-threshold segmentation algorithm. For this study, ground objects are those having nDSM values less than or equal to 0.5m.

Classification concentrated on ground objects because aquaculture structures can be found just above the lake water. Geometric attributes and relations to neighboring objects played significant roles in the process as classification relied to aquacultures' context.

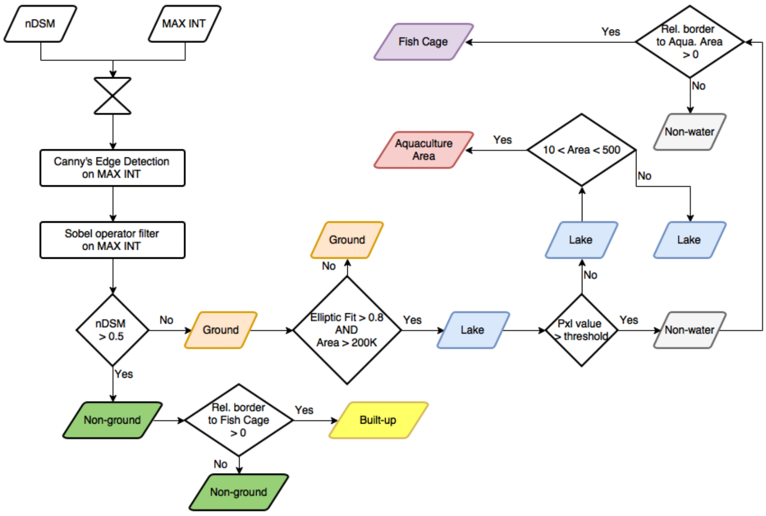
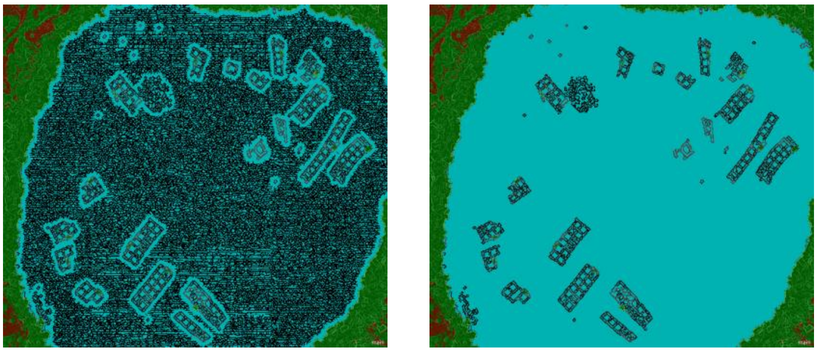


Figure 3. Workflow applied to extract aquaculture production area.

3. RESULTS AND DISCUSSION

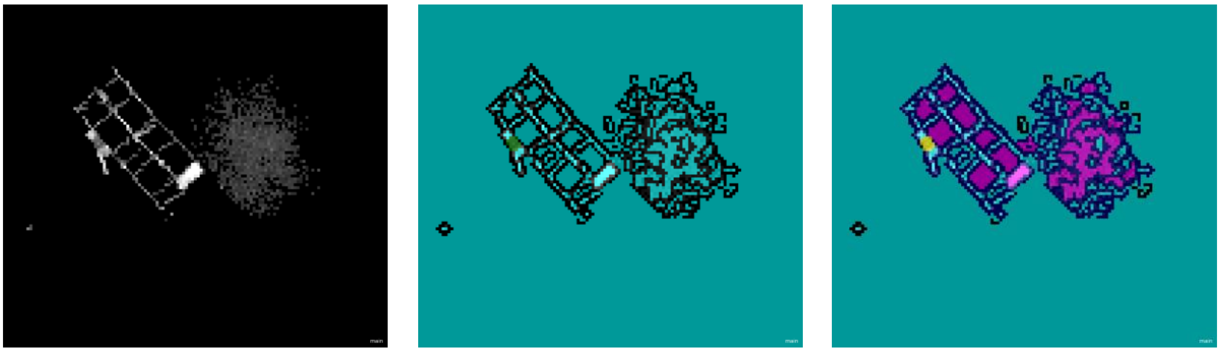
When the workflow was first applied only to MAX INT layer, it resulted to poor accuracy because not all aquaculture structures were classified; hence, the need to test on edge detected layers. For the first set-up, the edge layer derived using Canny's algorithm was utilized. Using multi-threshold segmentation algorithm, a threshold of zero was first used on the said layer resulting to a noisy classification of non-water objects (Fig. 4a). This happens because weak edges on water (probably ripples) were still detected. A higher threshold (0.05) was then chosen to achieve a satisfactory segmentation of aquaculture structures (Fig. 4b).

Testing a threshold value of zero on the edge layer derived using Sobel operator, the output was already satisfactory for the second set-up because no weak edges were segmented. With the application of the developed workflow, the aquaculture structures in the lake were extracted. Even if the producer's accuracy is 100%, the user's accuracy is slightly lower (90%) which can be attributed to the misclassification of other non-water objects as aquaculture, e.g. noise in the uncalibrated intensity data (Fig. 5). Nonetheless, a detailed classification resulted as fish cages, aquaculture area and built-up were delineated.



(a) Threshold = 0 (a) Threshold = 0.05

Figure 4. Segmentation on edge layer derived using Canny's algorithm entails proper selection of threshold value.



(a) Intensity layer with noise (b) Detected edges by Canny’s (c) Classified image

Figure 5. Noise/Error on the intensity layer can lead to misclassification of objects.

Although both edge layers performed very satisfactorily, the output of the Sobel-filtered layer generated a more precise geometry of the aquaculture structures compared with Canny’s (Figs. 6-7). It can be observed that some fish cages/fish pens have weak boundaries, resulting to weak edges. In some cases, aquacultures do not have closing and are therefore irregular in shape. Thus, post-processing methodology (Fig. 8) was introduced to improve the visual appeal of the classified image, as well as for the summary statistics of aquaculture production in the two lakes.

First, the exported feature was converted to polygon. Dissolve tool was then applied on all fish cages such that there is only one polygon for every fish cage. This tool removes multiple segmentation objects which form part of a single cage. In addition, polygons were reshaped to enclose some open spaces that were not delineated due to weak edge information. Misclassified objects due to errors inherent in the data were deleted. Also small open spaces inside the cage were filled in using the tool. To further improve the cartographic quality of the shapefile, smoothing was done using PAEK (Polynomial Approximation with Exponential Kernel) interpolation with a 3-m tolerance. Calculation of area was done at the end of the refinements.

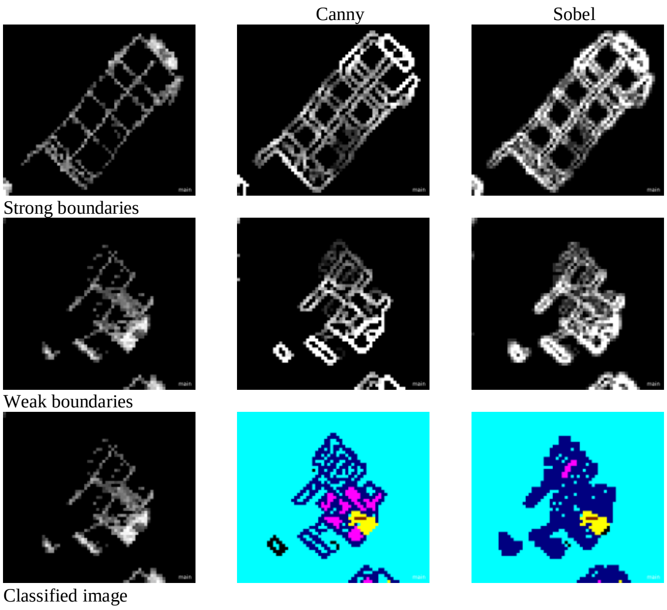
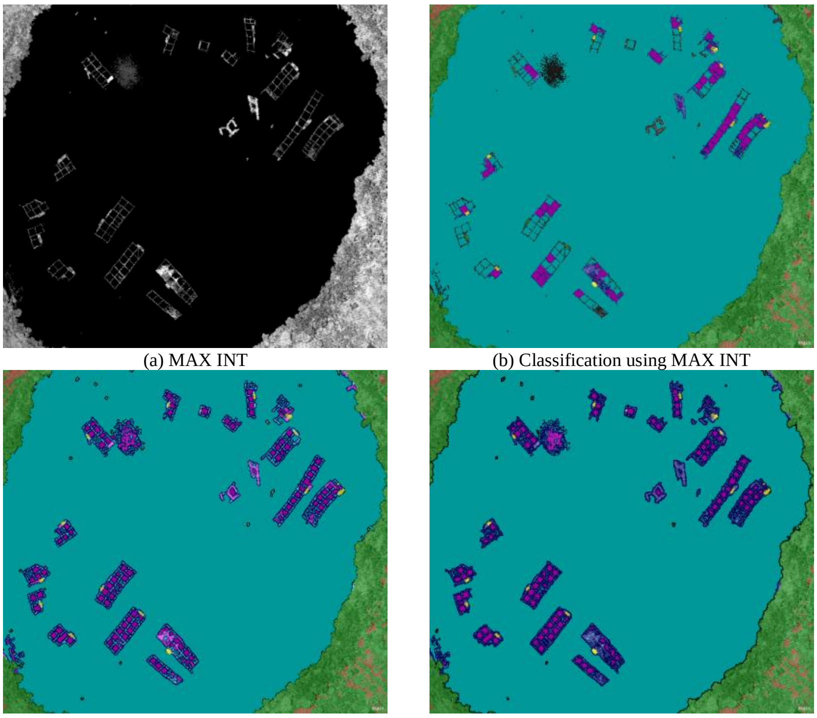


Figure 6. Comparison of outputs.

After GIS processing (Figs. 8-9), 18 aquaculture structures were identified in Tikub Lake with an approximate area of 10,556 m^2 or 1.05 hectares. This means that 2.3% of the lake is used in aquaculture production. For Gunao Lake, 19 aquaculture sites were extracted accounting to an approximate area of 17,978 m^2 or 1.80 hectares. This means that 7.68% of the lake is used in freshwater culture production. However, its accuracy can still be improved after further field verification as the spatial resolution will have effects on the actual area.

Overlaying the GIS file on Google Earth exhibits a potential application in change detection (Fig. 10). For Tikub Lake, a decrease in the number of aquaculture structures is apparent between 2001 and 2014. Comparing the extracted aquaculture to the 2015 image, slight expansion in some aquaculture areas is observed. The case is different in Gunao Lake as dynamic changes are observed: there are years where there was increase in the number of aquaculture, and otherwise. The final map of aquaculture (Fig. 11) can then be used as baseline information in the fisheries management of the two lakes.



(a) MAX INT (b) Classification using MAX INT

(c) Classification on edge layer using Canny edge (d) Classification on edge layer using Sobel filter

Figure 7. Comparison of outputs for aquaculture extraction in Lake Gunao.

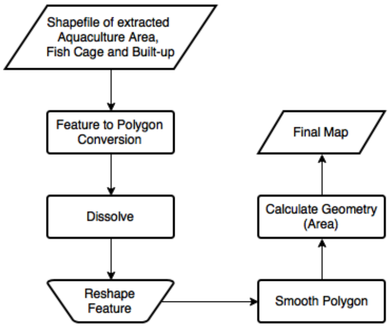
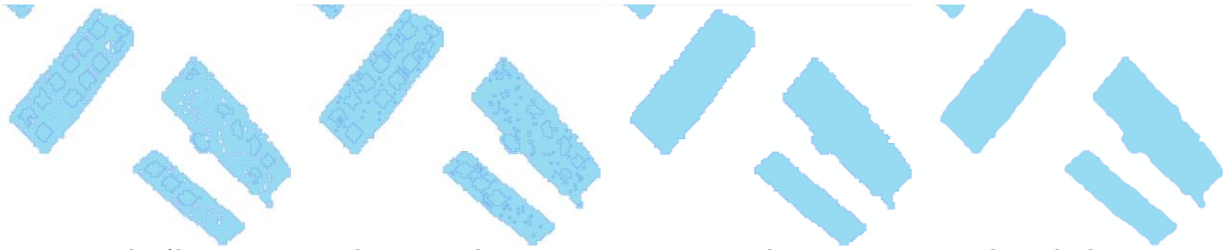
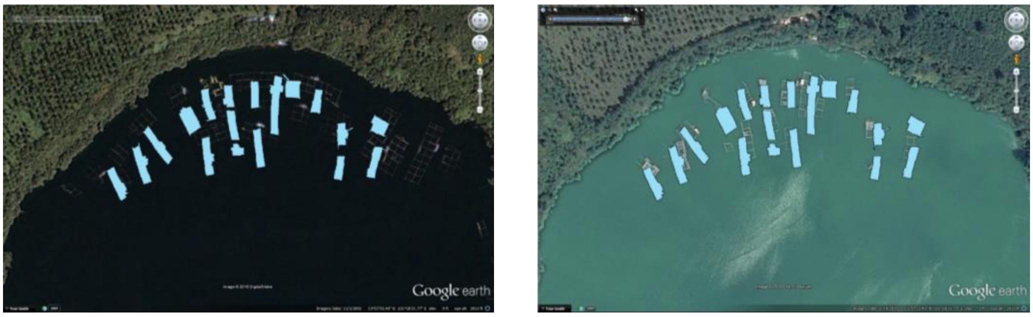


Figure 8. GIS post-processing steps.



(a) Raw shapefile (b) Feature to Polygon (c) Dissolve (d) Smooth Polygon

Figure 9. Output for GIS post-processing.



(a) 2001 Google Earth image (b) 2015 Google Earth image

Figure 10. Change detection in Tikub Lake.

4. CONCLUSION & RECOMMENDATION

This study presents a framework in mapping freshwater aquaculture production in two lakes located in Quezon Province, Philippines with the primary use of LiDAR intensity image as an alternative to satellite images and height metrics from LiDAR. Classification using intensity image alone results to lower accuracy, which can be solved by employing edge detection algorithms on it, e.g. Canny's method and Sobel operator filter. The use of geometric features and relations of object to its neighboring objects has been fundamental in classification. The method in this study enabled the extraction of all the aquaculture sites, with slight irregularities in geometry because of weak edge information. Hence, cartographic quality of the final map is enhanced by performing GIS post-processing. As found, the aquaculture production area in Gunao Lake is 17,978 m^2 (1.80 ha), and 10,556 m^2 (1.05 ha) in Tikub Lake.

ACKNOWLEDGEMENT: This study is funded by the Department of Science and Technology (DOST), and supported by the Mapúa Institute of Technology and Philippine Council for Industry, Energy and Emerging Technology Research and Development (PCIEERD) under the Phil-LiDAR 2 Program: National Resource Inventory of the Philippines Using LiDAR and other Remotely Sensed Data, headed by Dr. Ariel C. Blanco of UP-Diliman.

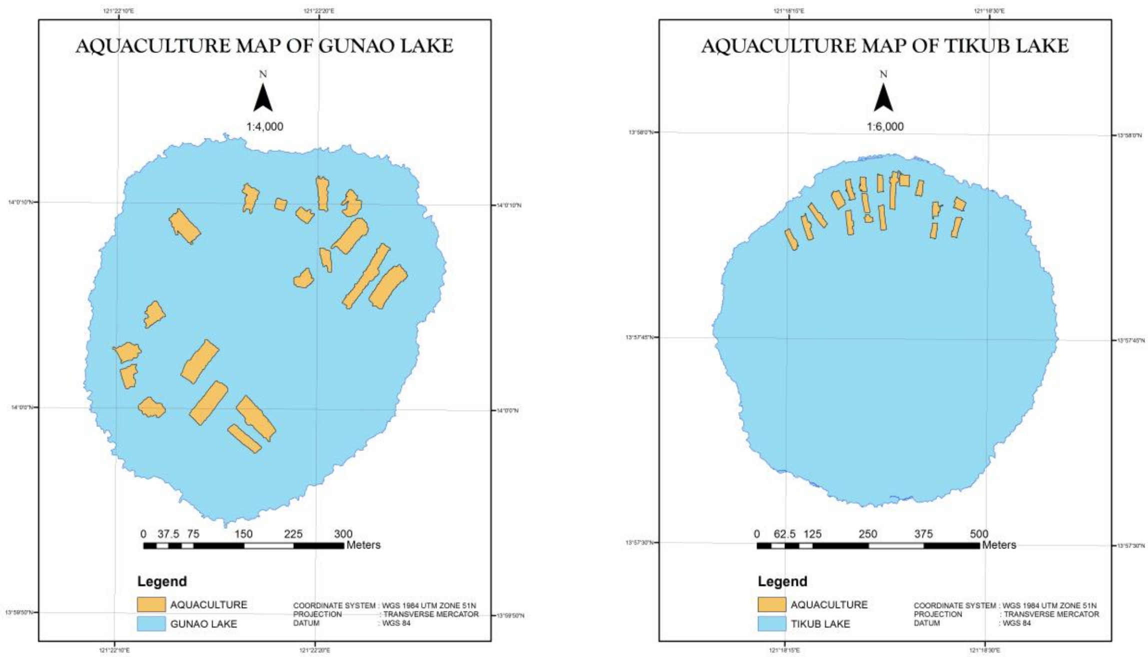


Figure 11. Aquaculture maps.

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