Aquaculture Feature Detection using Diwata-1 Satellite Image – Philippines' First Microsatellite Data

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ABSTRACT:

Over the decades, Philippines' coastal areas have experienced rapid and dynamic changes due to the increasing demands in aquaculture fisheries. With the advent of different remote sensing techniques in feature extraction and classification, a methodology was developed to extract fish pens and fish cages in Laguna Lake using the available ~60m resolution Diwata-1 SMI with LCTF satellite image. The application of different image enhancement techniques was explored to improve the quality of the image layers. To remove the redundancy of information, Principal Component Analysis was applied to the 8-band multispectral image. Gaussian Low Pass filtering was used to eliminate noise while Laplacian filtering enhanced the edges of the aquaculture features. Multiresolution segmentation and rule-based classification methods were found effective in extracting aquaculture features from the image. The techniques presented in this paper demonstrated the potential of Diwata-1 Satellite Image to detect and identify aquaculture features which can be a framework to utilize Philippines' first microsatellite data for studying and monitoring aquaculture areas and its effect on the environment.

1. INTRODUCTION

Laguna de Bay is the largest lake in the Philippines and one of the largest in Southeast Asia (Israel, 2007) with a surface area of approximately 90,000 hectares (Pullin, 1981). Surrounding the lake are urban areas such as Metro Manila and the provinces of Rizal and Laguna (Figure 1) inhabited by a rapidly growing population which depends on the lake's natural resources. There are approximately 3.5 million people residing in the lakeshore communities while over 14.6 million people depend on the lake's resources (Laguna Lake Development Authority, 2016). The lake is governed by the Laguna Lake Development Authority (LLDA) which is a public corporation established in 1966 to manage the lake's resources, drainage and flood control (Pullin, 1981). As defined by R.A. 4580, the mandated jurisdiction of the LLDA is 3,880 sq. km. which is significantly larger than the basin of the lake (2,920 sq. km.) (Laguna Lake Development Authority, 2016).

The fish pen industry was introduced in Laguna Lake as early as 1971 (Delmendo, 1987) when it was learned that fish species that are not native to its waters can be grown there (Israel, 2007). Fish pens are netted and fenced structures secured and conforming to the bottom substrate but still allowing free exchange of water (Travaglia, Profeti, Aguilar-Manjarrez, & Lopez, 2004). The LLDA first built a 38-ha pen and stocked 150,000 milkfish (Chanos chanos) fingerlings in the lake when the number of fish catch declined because of overfishing (Pullin, 1981). Fish pen and fish cage culture in the lake has since then flourished, providing a source of income and employment to the neighboring communities, public revenues to the government, and food to the consuming public (Israel, 2008). The number of fish pens increased from 38 has. in 1971 to 30,000 has. in 1983. In 2006, there was a total of 12,117 has of registered fish pens and fish cages in the lake with an average annual increase rate of 8.4% from 2000-2006 (Israel, 2007)

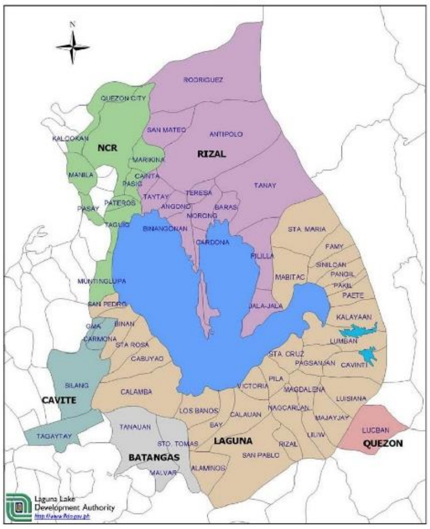


Figure 1. Laguna lake and its surrounding provinces and municipalities (Laguna Lake Development Authority, 1995)

Section 51 of Republic Act (RA) No. 8550 or the Philippines Fisheries Code of 1998 states that ten percent (10%) of the suitable water surfaces of all lakes shall be allotted for aquaculture purposes. The area of aquaculture in Laguna Lake surpasses the allowable extent. The LLDA and the Federation of Fish Pen and Fish Cage Operators Association of Laguna de Bay Inc. are dismantling and demolishing the structures and has an agreement with the fish pen operators to clear areas until December 31, 2017 ("Laguna Lake Development Authority," 2017).

There is a need for a cost-effective mapping and monitoring of aquaculture structures in Laguna de Bay but given the large extent of the lake, traditional methods of surveying can be difficult and tedious. Remote sensing using satellite imagery can be a solution to this problem. One of the advantages of remote sensing is being able to acquire data for a large area at minimal costing (Alexandridis, Topaloglou, Lazaridou, & Zalidis, 2008). Another advantage of using remote sensing is that the output of processing is digital data which can be incorporated into an existing Geographic Information System (GIS). Once incorporated into GIS, further spatial analysis can be evaluated for better planning and regulation of the structures.

In a study made by Han et. al., aquaculture structures were extracted from a Landsat 7 ETM+ image with a spatial resolution of 30m. The Independent Component Analysis (ICA) method which is an algorithm to separate mutually independent signals statistically from linear mixed signals was applied to the satellite image. An accuracy of almost 90% was achieved in detecting aquaculture features using this method (Han, Chi, & Yeon, 2005).

In the first quarter of 2016, Diwata-1 was launched from the International Space Station. It is a 50kg microsatellite with a payload subsystem containing a high-precision telescope (HPT), space-borne multi-spectral imager (SMI) with liquid crystal tunable filter (LCTF) and a wide field camera. The spatial resolution of each sensor is 3 meters, 80 meters and 7 kilometers respectively (PHL-Microsat, 2016). For this study, images acquired by the SMI with LCTF were used. The aim of this research is to detect aquaculture features from Diwata-1 multispectral images.

2. MATERIALS AND METHODS

There were eight (8) available images with different band ranges which intersect the area of interest. These images were acquired last April 11, 2017. The bands used were those that cover a part of Laguna Lake specifically bands centered at 550nm, 660nm, 670nm, 680nm, 710nm, 740nm, 760nm, 870nm. Images with banding were not considered in this research. The spatial resolution is 58.8 meters. Each image band was geometrically corrected and rectified into the Universal Transverse Mercator (UTM) Zone 51N. A subset was created to isolate the intersecting areas of the selected bands. Figure 2 shows the summary of methods used in extracting aquaculture features from Diwata SMI with LCTF imagery.

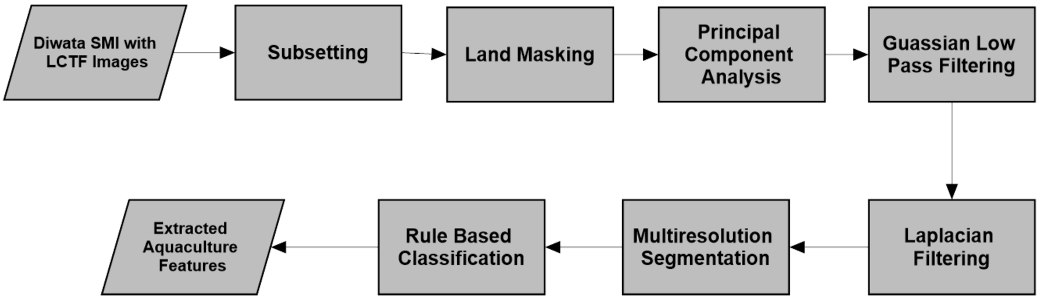
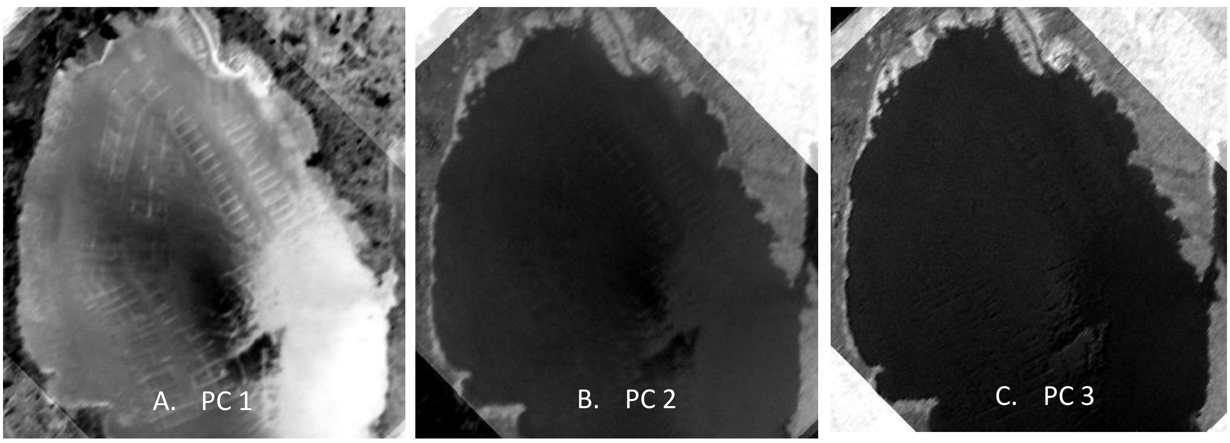


Figure 2. Flowchart of the extraction of aquaculture features from Diwata image

Principal Components Analysis (PCA), also known as the Karhunen Loeve transform or as the Hotelling transform was performed to remove the redundancy of information in the images. PCA is grounded on factorization method developed in linear algebra. It is usually used for classification and compression of data by employing statistical methods to eliminate less important information (Nixon & Aguado, 2012). Correlation between spectral bands arises from different factors such as material spectral correlation, topography and sensor band overlap (Schowengerdt, 2007). Table 1 shows the high correlation of the available bands. Through visual inspection and comparison of each PCA band, the aquaculture features were determined most visible in PC1.

Table 1. Correlation Matrix of the eight (8) spectral bands.

Correlation	550	660	670	680	710	740	760	870
550	1	0.683	0.536	0.369	0.15	0.561	0.856	0.731
660	0.683	1	0.831	0.645	0.388	0.901	0.536	0.743
670	0.536	0.831	1	0.808	0.547	0.763	0.367	0.57
680	0.369	0.645	0.808	1	0.752	0.58	0.194	0.392
710	0.15	0.388	0.547	0.752	1	0.358	0.008	0.184
740	0.561	0.901	0.763	0.58	0.358	1	0.549	0.768
760	0.856	0.536	0.367	0.194	0.008	0.549	1	0.785
870	0.731	0.743	0.57	0.392	0.184	0.768	0.785	1



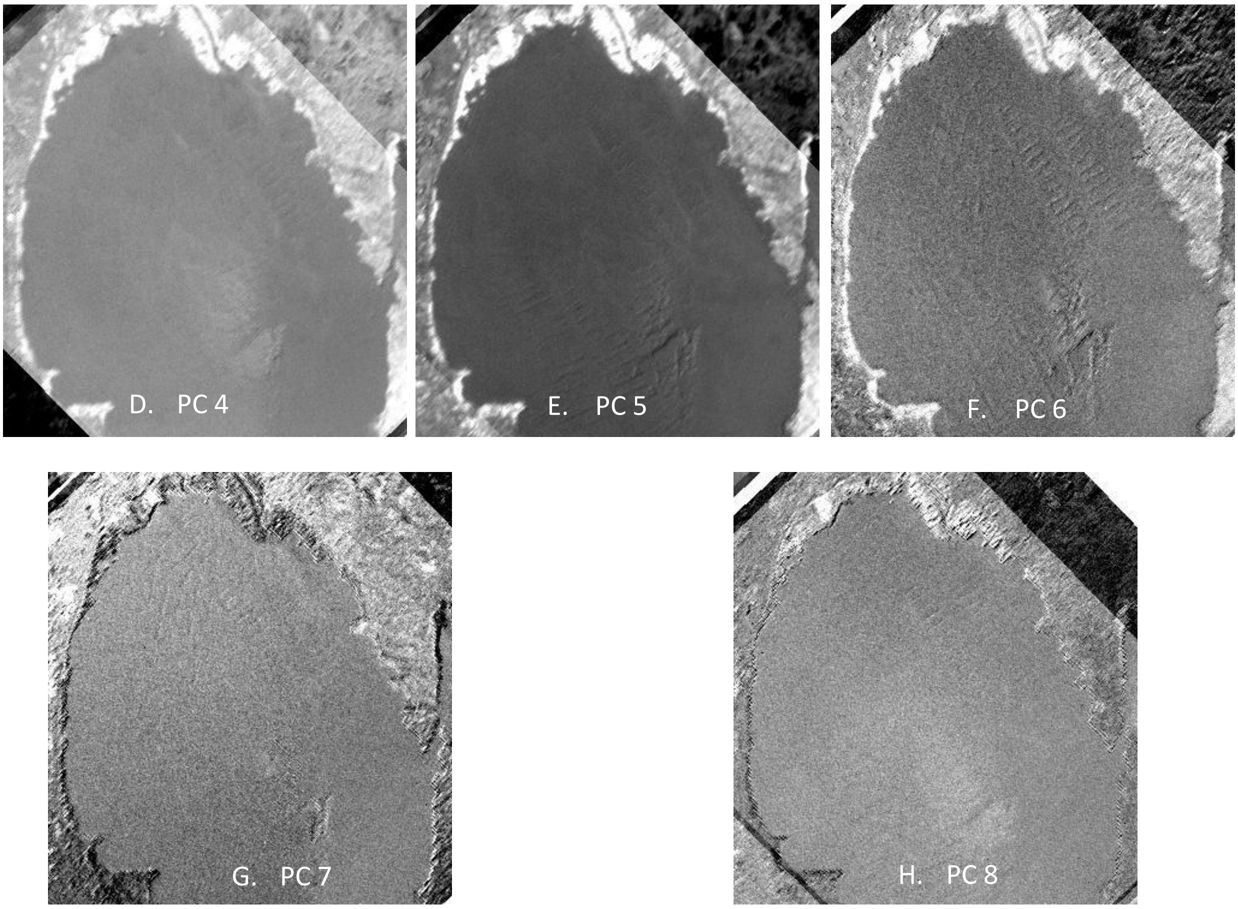


Figure 3. Principal Component Analysis (PCA) Output Images

Aquaculture structures are man-made features which are easily identifiable in satellite images because of their shapes. Such features can be enhanced using image filtering techniques. These techniques use filters or kernels which are applied to each pixel and its neighbors within the image. The problem with edge enhancement techniques is that is also enhances noise in the image. To eliminate the high frequency noise in the PC 1 band, a low pass 7x7 Gaussian filter (Figure 4) was applied to the image. Gaussian filters are similar to mean filters but it employs a kernel that represents a Gaussian bell.

0.0000	0.0000	0.0003	0.0006	0.0003	0.0000	0.0000
0.0000	0.0011	0.0079	0.0153	0.0079	0.0011	0.0000
0.0003	0.0079	0.0563	0.1082	0.0563	0.0079	0.0003
0.0006	0.0153	0.1082	0.2079	0.1082	0.0153	0.0006
0.0003	0.0079	0.0563	0.1082	0.0563	0.0079	0.0003
0.0000	0.0011	0.0079	0.0153	0.0079	0.0011	0.0000
0.0000	0.0000	0.0003	0.0006	0.0003	0.0000	0.0000

Figure 4. 7x7 Gaussian Low Pass Kernel

After eliminating the noise in the PC 1 band, Laplacian filter is utilized to improve the extraction of aquaculture features. This filter finds areas with rapid changes or edges in the image. The Laplacian based edge detection method looks for zero crossing in the second derivative of the image to find edges. Edges of features have higher pixel values compared to their neighbors. Gradient filters compare these values to a threshold to detect an edge. The first derivative shows the maximum value while the second derivative's output is zeros (Maini, 2009). For this research, a 7x7 Laplacian kernel (Figure 5) was selected and applied to PC 1 band.

0	0	0	-1	0	0	0
0	0	-1	-2	-1	0	0
0	-1	-2	-4	-2	-1	0
-1	-2	-4	44	-4	-2	-1
0	-1	-2	-4	-2	-1	0
0	0	-1	-2	-1	0	0
0	0	0	-1	0	0	0

Figure 5. 7x Laplacian Kernel

The bands selected for layer stacking were 550nm, 670nm, 760nm, PC1 and the output of the Laplacian filtering enhancement. A mask band for the land was created by using a threshold value in the NIR band (760nm) to eliminate areas not needed in this research. Water absorbs the signal in the NIR region more than terrestrial features thus signifying lower values in the NIR band to be most likely water. The created mask was then applied to the stacked image.

After applying spatial and spectral enhancements, multiresolution segmentation using eCognition software was utilized. A trial-and-error method was used in selecting weights to generate a suitable segmentation image. The weights given to the bands 550nm, 670nm, 760nm, PC1 and Laplacian filtered image were 1, 1, 3, 5, and 5 respectively while the values for scale, shape, and compactness were 20, 0.1, and 0.9 correspondingly. Through visual inspection, the aquaculture features were best segmented using these parameters.

Rule-based classification scheme was selected to classify the aquaculture features. First, a threshold value of > 100 was used for the mean values of the edge enhanced image. This selected most of the fish pens visible on the image. Relative to the border of masked land was used to eliminate objects classified with the same boundary as that of the land. Minimal manual classification was carried out to classify aquaculture features that remained unclassified.

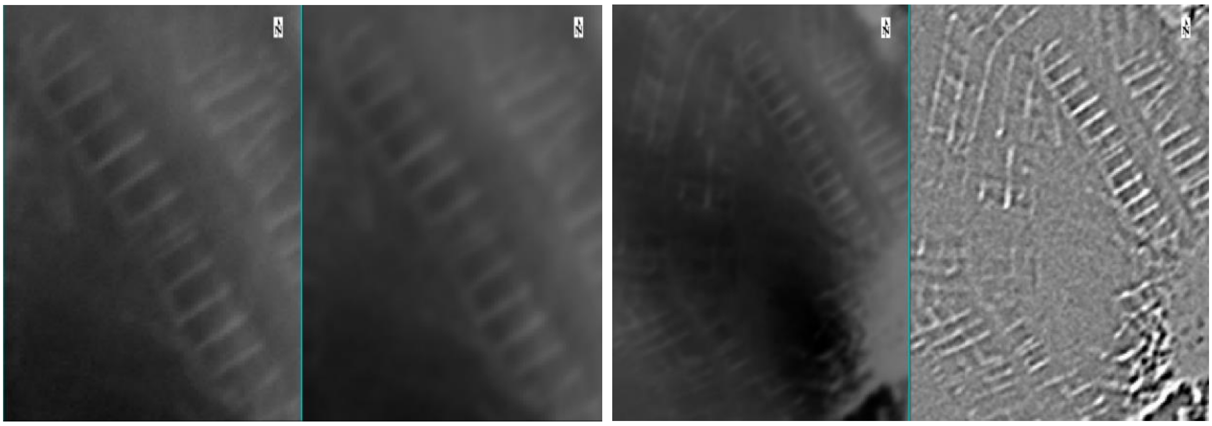
3. RESULTS AND DISCUSSION

There is a high correlation between the image bands as seen in Table 1. The highest of which is the correlation of bands 660nm and 740nm with 0.901. Bands 660nm and 670nm have a correlation of 0.831 which is plausible because of the nearness of the band ranges. The lowest correlation is 0.150 which is between bands 550nm and 710nm. The average of the correlation coefficients is 0.556 which justifies the use of Principal Components Analysis to reduce the redundancy of information.

Figure 6 (a) shows the zoomed in Principal Component 1 (PC1) band. The aquaculture features are more pronounced compared to the raw image but there are noises evident in the image. The Gaussian Low Pass filter (7x7) as seen in Figure 6 (b) reduced the noise and smoothened the appearance of the image. The disadvantage of using this filter is that it will lessen the effects of the edge enhancement technique but its capability to lessen the noise makes it valuable to this study. If the noise is not reduced, it will confuse the segmentation of the image and decrease the accuracy of extraction of features.

Laplacian filters are edge enhancement filters that produce sharper and better contrast images. Figures 6 c and d shows the transformation of the Gaussian low pass filtered image into a sharper image with pronounced boundaries. The objects are more distinguishable in the Laplacian enhanced image.

The bands stacked together were 550nm, 670nm, 760nm, PC1 and the output of the Laplacian filtering enhancement. The other bands were disregarded because of their high correlation with other bands. The multiresolution image produced using the stacked bands is seen in Figure 7a. A trial-and-error method was employed to determine the best segmentation parameters for aquaculture extraction. The man made features were suitably segmented using the selected parameters as seen in Figure 8a where patterns resembling boundaries of aquaculture are evident.



(a) (b) (c) (d)

Figure 6. (a) PC1 band, (b) enhanced PC1 band using a Gaussian 7x7 Low Pass filter, (c) Gaussian 7x7 Low Pass filter enhanced PC1 image, (d) Laplacian 7x7 filter enhanced output

The rule-based classification scheme eliminated most of the non-aquaculture features (Figure 7b) such as land and water. Unfortunately, not all aquaculture features in Laguna Lake were classified and the boundaries of the extracted aquaculture features were not delineated completely because of the limitations of the spatial resolution of the image.

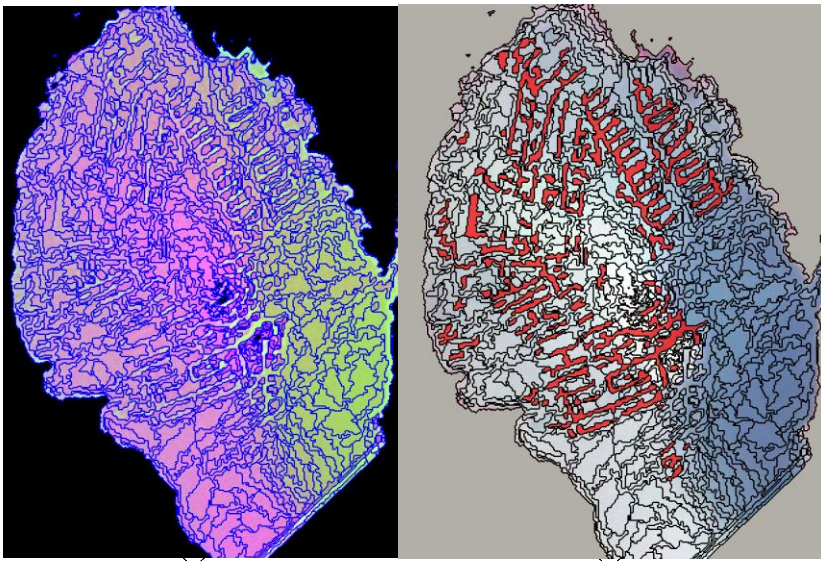


Figure 7. (a) Multiresolution Segmented Image, (b) Output of the Rule-based Classification

Assessing the accuracy of the aquaculture extraction using object based classification (Figure 8) was done by comparing the results with reference data. One of the limitations of this research is that no field data was acquired. Instead of field data, image interpretation was utilized to determine the aquaculture features detectable in the image which was used as reference information. Data that were gathered using visual interpretation include the number of extracted objects that have been correctly classified, number of extracted objects that have been wrongly classified, and the number of features that were not classified. But, it should be noted that delineation of aquaculture features using image interpretation is restrictive because of the limitation in spatial resolution.

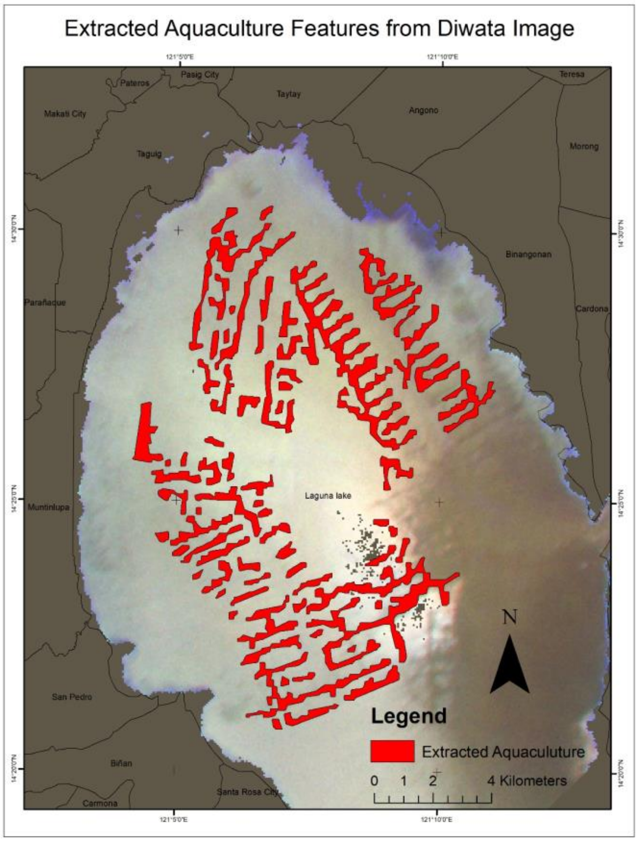


Figure 8. Map of the Extracted Aquaculture from a Diwata Image

A research by Zhan et al. (Zhan, Molenaar, Tempfli, & Shi, 2005) defined three measures of quality namely correctness, completeness and overall quality for accuracy assessment of object-based classification. The per-object measures of correctness and completeness were computed using the formulas below:

$$Correctness = \frac{N\,(C \cap R)}{N\,(C \cap R) + N\,(C - R)} \quad (1)$$

$$Completeness = \frac{N\,(C \cap R)}{N\,(C \cap R) + N\,(R - C)} \quad (2)$$

$$Overall\ Quality = \frac{N\,(C \cap R)}{N\,(C \cap R) + N\,(C - R) + N\,(R - C)} \quad (3)$$

Where:

$N\,(C \cap R)$ = number of features common to both classified and reference data

$N\,(C - R)$ = number of features that belong to classified data but not to reference data

$N\,(R - C)$ = number of features that belong to reference data but not to classified data

Based on image interpretation, there are 60 features which are both common in the classified and reference data, 5 features that belong to the classified data but not to the reference data and 21 features identified in the reference data but not in the classified data. Applying the formula by Zhan et al. will yield the following results (Table 2):

Table 2. Per-object Measure of Accuracy

Correctness	92.31%
Completeness	74.07%
Overall Quality	69.77%

4. CONCLUSION

Extraction of aquaculture features from a ~60m resolution image seemed impossible because of the limitation of identifiable objects from a low spatial resolution satellite image. The reason behind the possible detection of such features from the image is the time of capture of the data. It was acquired during the late afternoon which caused shadows of the boundaries of fish pens and cages to be cast on the water. These shadows and the edges of the aquaculture features caused the change in the spectral information of the pixels. However, these pixels are mixed pixels of the signature spectra of the water and the boundaries of the aquaculture features. Using a pixel based approach will confuse these pixels with other water pixels with different water quality or with other floating objects. The utilization of an object-based approach addressed this problem.

The application of Principal Components Analysis was beneficial in this research to remove the redundancy of information in the different bands which manifested in the correlation coefficients shown in Table 1. To further enhance the output of PCA, a Gaussian Low Pass filter was applied to lessen the noise in the image. Moreover, Laplacian filter was also applied to enhance the edges of the target features.

A rule-based multiresolution segmentation successfully identified and classified the aquaculture features. Comparing the results of the classified image to the reference data from image interpretation, an overall quality of 69.77%, correctness of 92.31% and completeness of 74.07% were achieved. It should be noted that all the boundaries of the features extracted were incomplete because shadows are only cast on one side of an object, making the other boundaries seem invisible on the image.

5. REFERENCES

Alexandridis, T. K., Topaloglou, C. A., Lazaridou, E., & Zalidis, G. C. (2008). The performance of satellite images in mapping aquacultures. *Ocean and Coastal Management*, *51*(8–9), 638–644. https://doi.org/10.1016/j.ocecoaman.2008.06.002

Delmendo, M. N. (1987). *Milkfish culture in pens: an assessment of its contribution to overall fishery production of Laguna de Bay*. ASEAN/UNDP/FAO Regional Small-Scale Coastal Fisheries Development Project.

Han, J., Chi, K., & Yeon, Y. (2005). Aquaculture feature extraction from satellite image using independent component analysis. *Machine Learning and Data Mining in Pattern Recognition, Proceedings*, *3587*, 660–666.

Israel, D. C. (2007). *The current state of aquaculture in Laguna de Bay*. PIDS Discussion Paper Series.

Israel, D. C. (2008). Fishpen and Fishcage Culture in Laguna de Bay: Status, Economic Importance, and the Relative Severity of Problems Affecting its Practice. *Philippine Journal of Development, 25*(1), 55–92.

Laguna Lake Development Authority. (1995). *Laguna de Bay Master Plan*.

Laguna Lake Development Authority. (2016). *Laguna de Bay Basin Master Plan: 2016 and Beyond*.

Laguna Lake Development Authority. (2017). Retrieved July 22, 2017, from http://llda.gov.ph/

Maini, R. (2009). Study and Comparison of Various Image Edge Detection Techniques. *International Journal of Image Processing*, *147002*(3), 1–12.

Nixon, M., & Aguado, A. S. (2012). *Appendix 3: Principal components analysis*. *Feature Extraction & Image Processing for Computer Vision* (Third Edit). Elsevier Ltd. https://doi.org/10.1016/B978-0-12-396549-3.00018-5

PHL-Microsat. (2016). PHL-Microsat. Retrieved July 23, 2017, from http://phl-microsat.upd.edu.ph/diwata1

Pullin, R. S. V. (1981). *Fish pens of Laguna de Bay, Philippines.*

Schowengerdt, R. A. (2007). CHAPTER 5 - Spectral Transforms BT - Remote Sensing (Third edition) (pp. 183–228). Burlington: Academic Press. https://doi.org/https://doi.org/10.1016/B978-012369407-2/50008-5

Travaglia, C., Profeti, G., Aguilar-Manjarrez, J., & Lopez, N. A. (2004). *Mapping coastal aquaculture and fisheries structures by Satellite Imaging Radar: Case Study of the Lingayen Gulf, the Philippines*. Food & Agriculture Org.

Zhan, Q., Molenaar, M., Tempfli, K., & Shi, W. (2005). Quality assessment for geo-spatial objects derived from remotely sensed data. *International Journal of Remote Sensing*, *26*(14), 2953–2974. https://doi.org/10.1080/01431160500057764