FISHPOND STATUS MAPPING USING RADAR REMOTE SENSING

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ABSTRACT:

The identification and monitoring of the status of all fishponds with Fishpond Lease Agreements (FLAs) in the Philippines is limited mainly to site visits. However, this approach is tedious, time-consuming, and costly due to the sheer number and locations of fishponds. This study explores the use of radar remote sensing in expediting the mapping of fishpond status (i.e., active, abandoned). Historical Sentinel-1A SAR images acquired from 2022-2023 covering identified fishpond areas were analysed. Several temporal statistics of their sigma nought backscatter values were calculated per polarization (i.e., VV and VH). Non-fishpond areas were masked out, and then Principal Component Analysis was applied to the stacked temporal statistics images. Afterwards, K-Means Cluster classification was applied to the first 7 components of the resulting PCA images to generate 4 classes. The resulting class with relatively low backscatter values is identified as water; "intermittent" water if their backscatter values vary greatly; and non-water or vegetated if their backscatter values are relatively high. Status was determined based mainly on the dominant class in each plot. Water class dominated plots are considered active; non-water or vegetated class dominated plots and plots that are covered mostly by "intermittent" water class are labelled as abandoned. Based on field-validated data, active fishponds, and old, abandoned fishponds (e.g., already have mangroves, or have no water control structures) were easier to correctly map, while abandoned fishpond with certain characteristics were harder to correctly identify. The approach is promising and can help BFAR map and monitor the fishponds in the country.

1. INTRODUCTION

1.1 Background of the Study

In the Philippines, Fishpond Lease Agreements (FLAs) represent contracts established between qualified applicants and the Philippine government. These agreements allow for the development of public lands covering a maximum of 50 hectares for a duration of up to 25 years, with the possibility of renewal for an additional 25 years (BFAR, 1979; BFAR, 2012). The primary governmental authority responsible for overseeing and regulating fishponds operating under FLAs is the Bureau of Fisheries and Aquatic Resources (BFAR). BFAR also holds the authority to determine the operational status of these fishponds, categorizing them as active, abandoned, or underutilized (BFAR, 2012). Typically, FLAs cover several fishponds that are developed in brackish areas that were formerly mangrove forests.

In general, fishpond status is determined based on their utilization and activities conducted by the lessee. Those that exhibit signs of occupation, possession, or operational activities, producing fish on a commercial scale (typically up to 1,500 kg of fish per hectare per year) are considered as "active" or "operational." Active fishponds are characterized by well-maintained dikes and functional water control systems, which play a crucial role in fish production activities. Conversely, "abandoned" fishponds are those that lack any indications of occupation, possession, or operational activities by the lessee, resulting in the absence of any signs of fish production operations. Lastly, "underutilized" fishponds are those covered by FLAs that have not yet reached full development or are not producing fish on a commercial scale within 3-5 years from the approval of their FLAs (BFAR, 2012). Fishponds classified as abandoned or underutilized can potentially undergo rehabilitation and conversion back into mangrove forest areas, (Duncan et al., 2016).

BFAR, the mandated agency overseeing fishponds with FLAs, relies mainly on on-site visits to assess their status. However, this approach is burdensome, time-intensive, and expensive given the large number and varied locations of fishponds in the country. In 2021, there were approximately 239,000 hectares of brackish water fishponds in the country, with over 15,300 hectares holding existing and valid FLAs (BFAR, 2021).

1.2 Objectives and Limitations of the Study

This research aims to explore the use of radar remote sensing in mapping fishpond status. More specifically, this study intends to establish a methodology to rapidly determine the status of identified fishponds (i.e., active or abandoned) using historical Sentinel-1 SAR images. Additionally, this research aims to investigate both the advantages and limitations of employing Sentinel-1 SAR images for the purpose of mapping fishpond status.

This study focuses on assessing the potential status of individual fishponds, and not the status of FLAs as this information is generally considered as classified and are not readily accessible to public. Moreover, the classification of active and abandoned fishponds will be based only on the observed physical characteristics attributable to such status, and not on their legal definition. Lastly, the vector files used to mask the fishponds was digitized on available Google Satellite Basemaps in QGIS.

2. REVIEW OF RELATED LITERATURE

2.1 Mapping Fishpond Status through Remote Sensing

Coastal Fishponds are bodies of water that are surrounded by dikes or earthen walls, which are typically half a meter to several meters wide, on all sides (Travaglia et al., 2004). Actual height of dikes depends on the characteristics of the site being

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developed, but they are designed to be significantly higher than the highest tide and flood levels that occur in the area (dela Cruz, 1983).

Optical satellite images have been used extensively in mapping fishponds as they can provide high accuracy and rich information on characteristics of fishponds (Wang et al., 2022). Landsat images have been used to determine the extents of developed fishponds in several sites in the past 30 years (Rajandran et al., 2022). Meanwhile, another study used Sentinel-2 images to conduct a global fishpond mapping and generated outputs that are consistent with the figures published by FAO (Wang et al., 2022). However, one significant limitation of Landsat and Sentinel-2 datasets is their inability to detect small-scale fishponds due to their resolution of 10-30m (Yu et al., 2020). While there are very high-resolution optical images, these datasets have limited historical archives and are expensive to acquire, which make them impractical to use for large-scale and multi-temporal mapping activities. Another key limitation of optical images is the presence of clouds especially during monsoon season, which limits the available images that can be used for analysis (Yu et al., 2020; Wang et al., 2022).

Radar remote sensing is a type of remote sensing system that utilizes the microwave region of electromagnetic spectrum. Space-borne radar remote sensing systems are designed as synthetic aperture radar or SAR systems, which capitalizes on the platform's movement in generating good resolution images. Some of the advantages of radar remote sensing over optical remote sensing, they are typically not affected by clouds, and they are active systems wherein they can capture even during night-time (Richards, 2009).

Sentinel-1 is a SAR satellite that was launched last 2014 and is operated by the European Space Agency (ESA). This satellite regularly captures C-band SAR images every 12 days with a medium spatial resolution of approximately 10-15 meters. ESA distributes Sentinel 1 SAR images as free and opensource datasets (ESA, 2023).

Multi-temporal Sentinel-1 SAR images have been used extensively in accurately mapping fishponds. One study discussed how these datasets were used to map fishponds in China and Vietnam with around 83% overall accuracy (Ottinger et al., 2017). Another study showed how historical Sentinel-1 images were also used map fishponds in the coastal areas of Vietnam with an overall accuracy of approximately 90% (Sun et al., 2020). One study utilized free historical Sentinel-1 SAR images, along with the also free and opensource Sentinel-2 multispectral optical images, in detecting over 3.4 million fishponds in the coastal zones of South Asia, Southeast Asia, and East Asia, which covers more than 2 million hectares (Ottinger et al., 2022). Clearly, these studies demonstrate the potential of Sentinel-1 SAR images in the applications of fishpond mapping.

Many research studies have already delved into the utilization of remote sensing for the purpose of identification and mapping fishponds. However, there is a scarcity of literature that explores the application of remote sensing, including radar remote sensing, specifically for detecting and mapping the status of fishponds. There is one study wherein it investigated the application of LiDAR datasets in assessing the status of brackish fishponds and achieved promising results (Cabanlit et al., 2016). However, the limited availability of LiDAR datasets constrains the practicality of this approach for routine and large-scale mapping operations.

2.2 Radar Response of Fishponds

In radar imagery, a fishpond typically presents as a dark feature enclosed by a bright rectangular outline, which constitutes the pond dikes (Ottinger et al., 2017). The darkness of fishponds in these images arises from their water surfaces having very low radar backscatter, which is a result of their radar signals being specularly reflected (Travaglia et al., 2004; Richards, 2009). On the other hand, the brightness of the pond dikes is due to the radar signal undergoing a double bounce interaction between the water surface and the dikes, which are nearly perpendicular to each other. Objects exhibiting this double bounce phenomenon have very strong backscatter response, thus appearing bright in synthetic aperture radar (SAR) images.

Active fishponds generally have well-maintained dikes and functional water control systems, which help maintain a certain level of water inside the pond structure. The well-maintained dikes of active fishponds are expected to continuously appear as contiguous, bright, typically rectangular outline. On the other hand, the consistent water level of active fishponds implies that they are expected to exhibit consistent low backscatter values for most of their operational cycle.

Abandoned or disused fishponds are ponds that do not have signs of fish production operations. Obvious signs of fishpond abandonment or disuse include the unmaintained, broken or breached dikes, and the non-functional water control systems. The lack of functional water control systems implies that the water level inside the ponds is no longer maintained and could already be subjected to regular tidal inundations. Another obvious sign of abandonment is the mangrove regrowth inside the ponds.

The radar response of abandoned fishponds can vary depending on the actual conditions of the ponds. Fishponds that have mangrove regrowth or recolonization will already exhibit volumetric scattering, which yields higher backscatter values than water surface. As such, mangrove recolonized ponds will already appear bright similar to any vegetated areas. On the other hand, ponds that are subjected to tidal inundations will have varied intensities depending on the current level of inundation. Specifically, if the tide is high during image acquisition, then this pond will appear dark. However, if the tide is low, the pond may become fully drained, which will then exhibit relatively brighter backscatter values. Lastly, fishponds with broken dikes will appear as bright polygons with gaps, which are indicative of the sections with the dike broken.

3. METHODOLOGY

The proposed methodology in this study is to first determine certain temporal statistics of stacked historical Sentinel-1 SAR images. Afterwards, PCA and an unsupervised classification to determine the potential status of the identified fishponds. The approach hinges on the assumption that the computed temporal statistics can help determine the difference in backscatter response between active and abandoned fishponds.

3.1 Study Area

The study site (Figure 1) covers the fishponds located in Batan Bay in the province of Aklan, Philippines. Batan Bay is in several municipalities, namely, Altavas, Balete, Batan, Cabugao, New Washington, and Tabon. This area, also known as the New Washington-Batan Estuary, was once a thriving fishing region.

However, there has been a consistent decrease in shrimp catch in the area, which is linked to factors such as the transformation of 76% of its mangrove cover into fishponds and a significant 400% rise in the use of fishing gear since the 1990s (Altamirano, 2010; Altamirano et al., 2014). It is estimated that approximately 24% of the fishing gears in Batan Bay operate illegally (Altamirano, 2010).

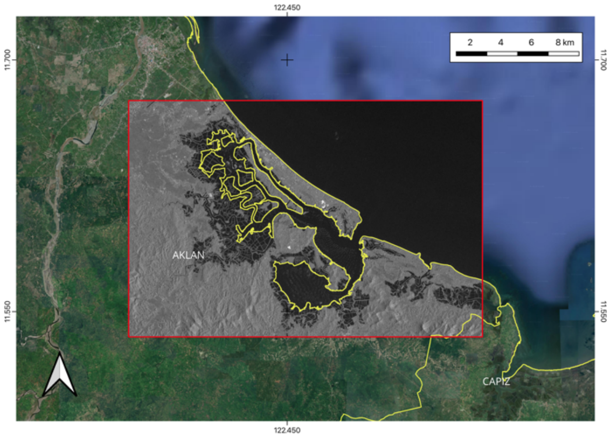


Figure 1. Vicinity map of the chosen study site, Batan Bay, which is in the province of Aklan, Philippines. A sample temporal median image of Sentinel-1 SAR images is overlayed to show the extent of the SAR images (red box) used in the study.

3.2 Data Sets Used

3.2.1 Sentinel-1 SAR images. ESA's Sentinel-1 SAR images acquired from September 2022 to September 2023 were used in this study. These SLC products were retrieved from ESA's Copernicus Open Access Hub. Details on some of the acquisition parameters of these images are shown in Table 1.

Satellite	Sentinel-1A
Product Type	SLC
Acquisition Mode	Interferometric Wide (IW)
Antenna Look	Right
Relative Orbit	134
Acquisition Time	~5:30 AM PST

Table 1. Acquisition parameters of the Sentinel-1 SAR images used in this study.

3.2.2 Field Validation Datasets. A field validation activity was conducted from September 16-18, 2023, wherein several fishponds which visited to confirm their actual status. Data and information recorded during this field activity include the observed physical conditions of the visited fishponds, and the actual status as confirmed through an interview of locals, caretakers or owners present during the visit. The observed conditions are used to determine the assumed status of the fishponds in case there is no local, caretaker, or owner present during the visit. Table 2 summarizes the assumptions used in determining the status of the fishponds in case no person can confirm their actual status.

In addition to the physical condition of the ponds, information on the fishpond operations were also recorded especially during interviews. Specifically, this information includes the duration of rearing cycle, e.g., how long does it take to rear the stock, and how long is the pond preparations. Information on the uses of fishpond plots, and the operations of the water control structures were also asked. Photographs of the visited fishponds were also taken for documentation purposes, and as additional data that can be used to validate the recorded statuses.

Active Fishponds	Abandoned Fishponds
Maintained dikes	Broken or breached dikes
Working water control system	Non-functional water control system
Maintained water level	Water level depends on tide
No mangrove regrowth inside pond	Pond is recolonized by mangroves

Table 2. Summary of the assumed characteristics of the fishpond status. The status of a visited fishpond will depend on these criteria in case no person is able to confirm the status.

3.2.3 Ancillary Datasets. Other SAR and optical images were also used as ancillary data in this study. These datasets include several NovaSAR-1 S-band SAR images, and a WorldView imagery. These images were acquired through the Synthetic Aperture Radar and Automatic Identification System for Innovative Terrestrial Monitoring and Maritime Surveillance or SARwAIS Project, and the Philippine Earth Data Resource and Observation Center or PEDRO Center of DOST Advanced Science and Technology Institute (DOST-ASTI). Additional details of these datasets are shown in Table 3.

	NovaSAR-1	WV-3
Type	S-Band SAR	8-band Multi-spectral
Spatial Resolution	~6m (resampled to 2.5m)	1.24m
Acquisition Time and Dates (PST)	10AM, 20 Dec 2020 10 PM, 10 July 2022 10 PM, 23 July 2022	10AM, 19 Sept 2023

Table 3. Additional information on the acquired ancillary images that were used in this study.

Other ancillary data include the shapefiles of the estimated plots of fishponds in the site. These features were digitized through a QGIS software wherein Google Satellite imagery was loaded and overlayed through it QuickMapServices plug-in and was used as a base map (QGIS.org, 2023). These ancillary datasets were used primarily in the analysis of the results.

3.3 Processing and Analysis Workflow

This study employed several data pre-processing and analysis steps to derive a fishpond status map (Figure 2). Many of these processes, especially the pre-processing, and parts of the SAR Image Classification processes, were done using Python Scripts that were run in a virtual machine, which were accessed through the High Performance Computing (HPC) service of DOST-ASTI's Computing and Archiving Research Environment (COARE).

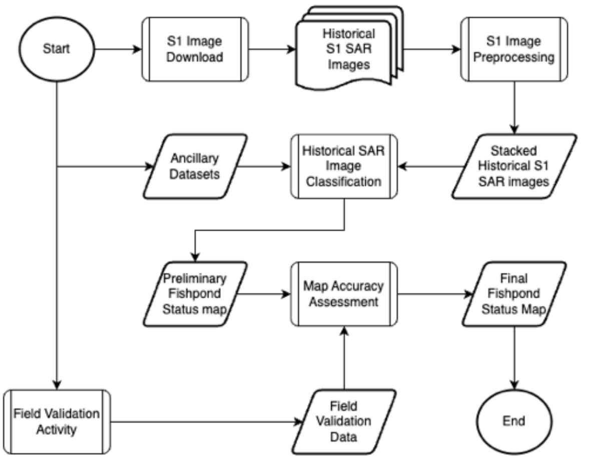


Figure 2. Processing and analysis workflow used in this study.

3.3.1 Sentinel-1 SAR Image Pre-processing. The downloaded Sentinel-1 SAR SLC products require pre-processing to derive their analysis-ready versions. Pre-processing these datasets started with the application of their corresponding updated orbit files, which helped improve the positional accuracy of the image. This was followed by radiometric calibration wherein the DN values of the downloaded images were transformed into their corresponding intensity values in the sigma^0 calibration. Afterwards, Multi-looking was applied, which helped reduce the speckle noise inherent in the image. This step was then followed by terrain correction, which reduced or removed the distortions due to terrain effects, and resample the image into 10m resolution. This step also geocoded the SAR image, which provided the appropriate map coordinates to the image. A subset was then extracted to focus only on the area that covers the target site. All of the abovementioned steps were applied to every downloaded Sentinel-1 SAR images. Separate files were generated per polarization, i.e., VH and VV polarizations. Once this was done, the pre-processed products were coregisted to derive the stacked pre-processed, historical Sentinel-1 SAR images, with one file per polarization. Figure 3 shows the overview of the pre-processing steps done.

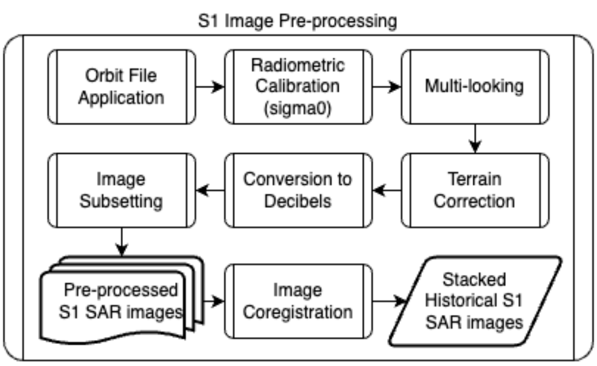


Figure 3. Sentinel-1 SLC product pre-processing workflow

3.3.2 Historical SAR Image Classification. In the historical SAR mage classification step, the temporal statistics images (e.g., mean, median, standard deviation, 1st and 3rd quartile, and the 5th and 95th percentile) were computed and generated per polarization stack. This process generated an image file containing seven bands corresponding to the computed temporal statistics. The stacked temporal statistics images per polarization were then merged into one file. Principal Component Analysis (PCA) was then applied to the generated merged file to reduce the dimensionality of the input data (Jolliffe and Cadima, 2016). Afterwards, K-Means Cluster, an unsupervised classification, was applied to first 7 components (Arcorace, et al., 2023). The classification was focused only on the areas within the digitized fishponds and was set to generate 4 clusters or classes after 50 iterations. These steps were done using Python scripts and the built-in functions and tools of SNAP 9.0.

The features that the four classes represent were assumed based on the observed dominant statistical values of these classes. The class with low standard deviation and low median backscatter values is assumed to represent consistent "water"; "vegetated or with mangroves" if it has high median backscatter but low standard deviation values; "intermittent waters" if the standard deviation is high. Table 4 shows the summary of the observed dominant statistics values and the assumed fishpond status that will be assigned to the class. Figure 5a-5c shows the sample images of the observed dominant statistical values per class that are being described in Table 4.

Dominant statistical values	Classification
Low standard deviation and low median/mean backscatter	Consistent water
Low standard deviation and high median/mean backscatter	Vegetated / with mangroves
High standard deviation	Intermittent waters

Table 4. Summary of the observed dominant statistical values that are used to assign the features of the four classes derived from the K-Means Cluster Classification.

Status of fishponds is then determined based on the dominant classes per plot. Plots that are dominated by consistent "water" class are assumed to be active. Otherwise, they are assumed as "abandoned". The acquired other SAR and optical datasets were then used to determine any potential misclassifications in the preliminary fishpond status map. Figure 4 provides an overview of the processes done during the historical SAR Image Classification.

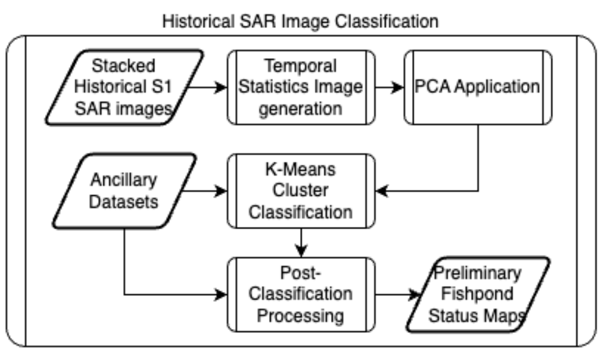
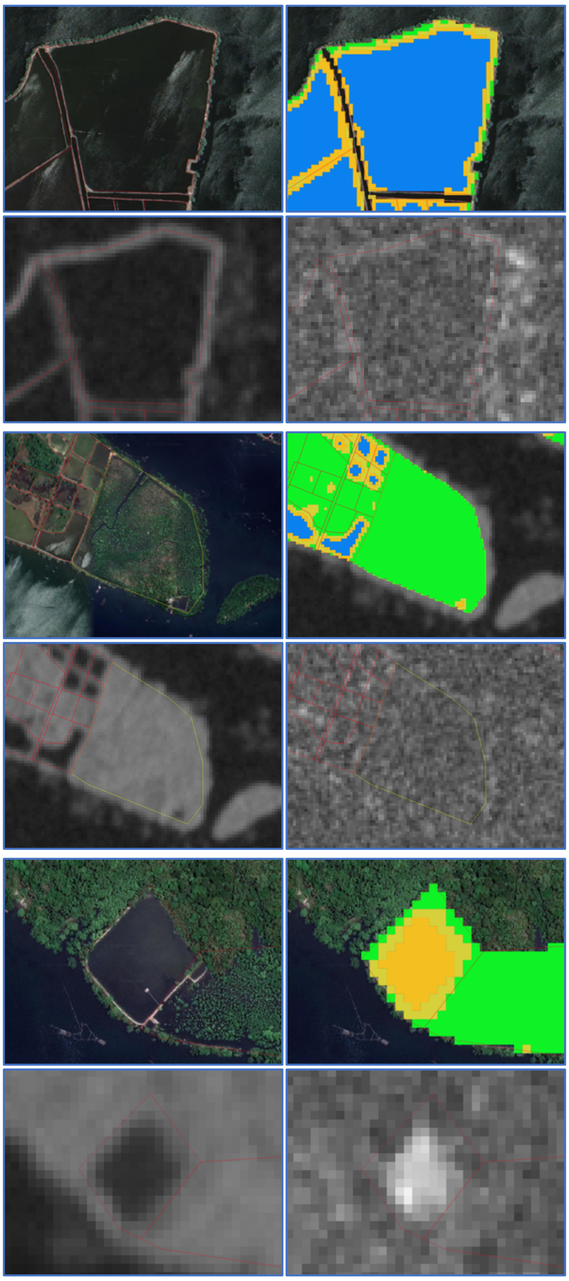


Figure 4. Processes done during Historical SAR Image Classification.



(a)

(b)

(c)

Figure 5. Sample images showing the observed dominant statistical values in Table 4: a. active fishponds, b. ponds with vegetative (mangrove) cover, and c ponds with apparent intermittent water. The images per set (clockwise, starting from top left) are optical, classification overlay, median, and standard deviation.

3.3.3 Accuracy Assessment. The accuracy of the generated fishpond status map was determined using the gathered field validation datasets. The statuses of the visited ponds were compared with their corresponding statuses that were derived from output of the unsupervised classification to determine the user's, producer's, and overall accuracy of the classification. The Kappa statistics were also computed help assess better the performance of the methodology.

4. RESULTS AND DISCUSSIONS

4.1 Processed SAR Images

A total of 29 SAR images were downloaded, pre-processed, and stacked per polarization. From these stacked images, temporal statistic images per polarization were successfully generated and stacked into a single file. PCA bands were also generated from the stacked statistic images. Sample outputs of the Median VH image and PCA band 1 are shown in Figure 6.

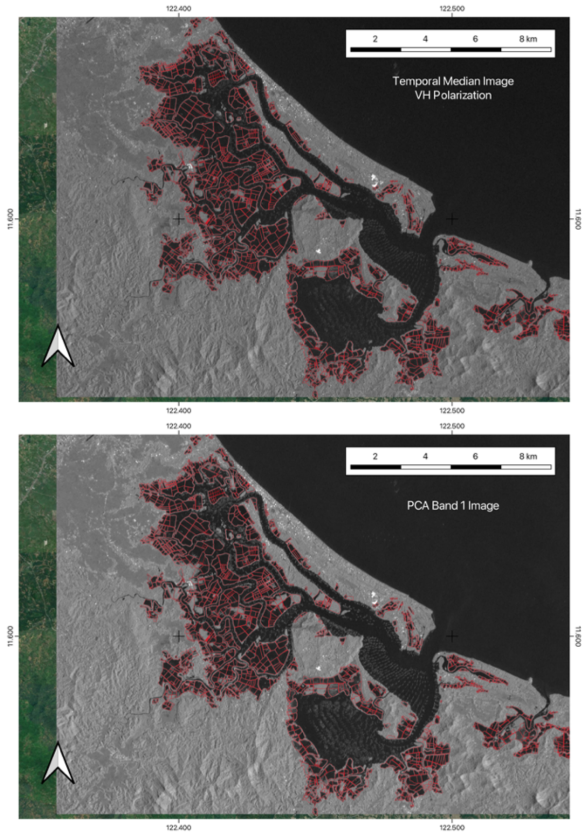


Figure 6. Generated temporal median image of VH polarization (top) and the generated PCA band 1 (bottom). Both images are visually identical, implying that the PCA band 1 captures mainly the information provided the median and probably including the mean images. Outline of digitized fishponds are overlayed to show their estimated extents.

4.2 Preliminary Fishpond Status Classification

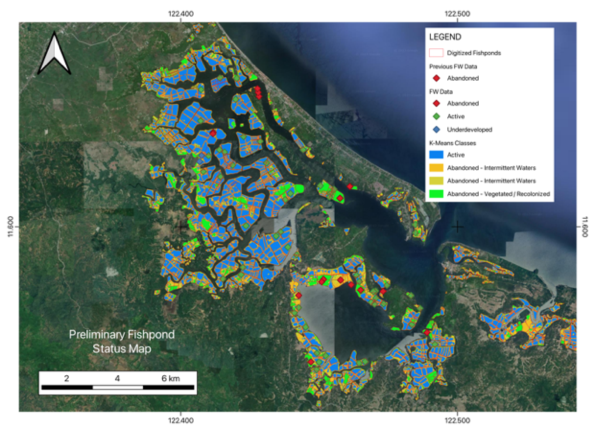


Figure 7. Preliminary Fishpond Status Map. Fieldwork (FW) data are overlaid for quick comparison with the derived classes.

From the first seven PCA bands, four classes were successfully generated through the unsupervised K-Means Cluster Classification. Figure 7 shows a preliminary fishpond status map based on the output of the unsupervised classification. Classes assigned in blue color are potentially active or operational ponds; classes in green color are assumed as abandoned as they correspond to potential presence of vegetation like mangroves; and classes in light orange or beige color are assumed also as abandoned due to potential variation in water levels attributable to non-functional water control systems or broken and unmaintained dikes.

4.3 Field Validation Data

Figure 8. Photos taken during the field activity. Upper left photo shows an active pond with algae; upper right photo shows an apparently abandoned fishpond with a small break on its dike that is not yet detectible in satellite images; lower left photo shows an old, abandoned fishpond with significant mangrove regrowth; lower right photo shows the water gate and dike remnants of an old, abandoned fishpond. Photo was taking inside the pond.

During the field activity conducted from September 16-18, 2023, a total of 52 ponds were visited and their status validated through observation of their current physical conditions, or through confirmation from owners, caretakers, or any locals who were present at that time. The target ponds were initially selected at random. However, during the actual field activity, priority was given to apparently abandoned fishponds. Of these 52 visited ponds, the status of 31 ponds were confirmed only through visual inspection, while the status of the remaining 21 ponds were confirmed primarily by caretakers who were present. When such persons were present, additional information on the fishpond operations were also asked and recorded. Figure 8 shows photos taken during the field activity.

At the end of the field activity, 35 of the visited ponds were confirmed as active, 15 were confirmed as abandoned, and 2 were tagged as apparently undeveloped sections, which was confirmed during interviews. To augment these points, data from a previous field activity that was conducted almost a year prior were also used. This contains 21 points, 19 of which are tagged as active ponds, and the remaining two are abandoned ponds, which were also visited in the most recent field activity. Table 5 shows a quick summary of the visited ponds during the field activity.

	Sept 2023 Field Work	**~ Q4 2022 Field Work**	**Total Ponds**
# visited ponds	52	21	73
# active ponds	35	19	54
# abandoned ponds	15	2*	15
# underdeveloped ponds	2	0	2
# ponds confirmed by locals	21	0	21
# ponds confirmed visually only	31	21	52

Table 5. Quick summary about the visited ponds. *These ponds have been visited in both field activities. Hence, they were not included in the total count.

4.4 Accuracy of the Preliminary Fishpond Status Map

When calculating the accuracy of the generated map, only active and abandoned fishponds were considered because there were no classifications available for underutilized or underdeveloped ponds. Additionally, the field data included only two ponds labelled as underdeveloped, which is an insufficient number of sample points for computation. Consequently, these points were excluded from the analysis.

Error Matrix		Reference Data			
		Active	Abandoned	total	User Accuracy
Classification	Active	51	6	57	89.5
	Abandoned	3	9	12	75.0
	total	54	15	69	
	Prod Accuracy	94.4	60.0		87.0
k = 0.59					

Table 6. Computed Error Matrix of the classification.

Based on the comparison between the 69 field validated data points and the classification data, the computed producer's accuracy of active and abandoned fishponds is 94.4% and 60%, respectively; the user's accuracy for the active and abandoned fishpond classifications is 89.5% and 75%, respectively. The overall accuracy is approximately 87%. However, it should be noted that this value is possibly influenced by the active fishpond classes that has significantly higher number of sample points compared to the abandoned fishpond class. Lastly, the computed Kappa Statistic is only around 0.59, which suggests that the classified image and the field data has a moderate agreement with each other (Rwanga and Ndambuki, 2017). Table 6 shows the summary of the computed accuracies.

The relatively high accuracy for active fishponds can be attributed to the strong correlation of their backscatter values, and their operation activities, which include 4-6 months of stock rearing and harvesting, followed usually by one month of pond preparation, which requires the complete pond drainage. This cycle of fish production activities implies that the pond is inundated or has water for most of the time, which in turn implies that active fishponds will have low median backscatter values, and low standard deviation values.

4.5 Challenges Encountered

4.5.1 Errors in the Classification. The errors in the classifications of active fishponds are due mainly from the presence of significant vegetation cover in some active ponds. This vegetation cover provides higher backscatter response compared with water surface, which is considered as an indicator of abandonment. There are ponds also that are intended for algal growth, which are then used to feed the reared fish stock. The algae in these ponds can become too thick that they already protrude above the water surface. This can also cause these ponds to have stronger backscatter response. Hence, if such pond stays in that state for a prolonged period, there is a possibility that will be erroneously classified as abandoned.

The inaccuracies in the abandoned fishponds classification can be attributed to the slow and gradual development of signs indicating abandonment. For instance, the regrowth of mangroves may take several years before becoming highly visible in satellite images. Additionally, damage to the dikes or water control systems may require several months or even years to become noticeable in satellite images, particularly those with medium spatial resolution. The presence of mangroves growing along the dikes, as observed during fieldwork, can also render breaks and damages in the dikes nearly impossible to detect in satellite images unless they are significantly larger than the image's spatial resolution. Lastly, some abandoned fishponds may remain consistently inundated year-round, regardless of tide level variations, making them appear active due to their continued low backscatter values and low standard deviation.

4.5.2 Limitations of Sentinel-1 SAR Images. While Sentinel-1 offers a valuable archive of free SAR images, which is beneficial for studies requiring historical context, its spatial resolution presents a significant challenge, particularly in this research. Smaller fishponds and elongated ones are often challenging to detect in these datasets, especially when their width spans only a few pixels. In such cases, the water surface of these ponds is frequently either entirely obscured or barely visible in the images due to the dominant radar response from their dikes, particularly those covered by substantial vegetation. Consequently, mapping the status of these fishponds using this dataset is virtually impossible or likely to yield inconclusive results. Additionally, damage to dikes that is not significantly larger than the image's resolution generally goes undetected. Figure 9 illustrates an example of an abandoned fishpond in such a situation.

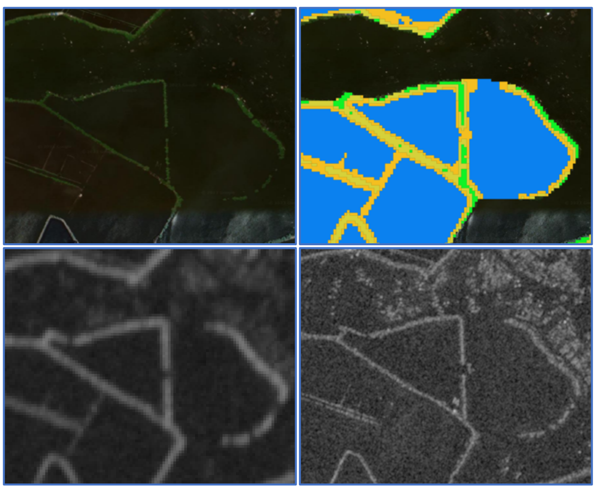


Figure 9. Sample of an abandoned fishpond (the one triangular) that was classified as active (upper right). This pond is generally inundated, and its apparent dikes are basically the mangroves that grew on those dikes. The dike gap appears blurry in Sentinel 1 data (lower left). A NovaSAR-1 Stripmap image provided a clearer view of this gap (lower right). A high-resolution optical image (Google Satellite Basemap in QGIS) also shows the gap in more detail (upper left).

To address this limitation, higher-resolution images, whether optical or SAR, may be employed to verify the existence of such damage. NovaSAR-1 can be a cost-effective alternative, given that the country has access to 10% of its imaging capacity (DOST-ASTI, 2019; Vicente et al., 2020).

4.5.3 Dynamics of Fishpond Operations. The ever-changing nature of real fishpond operations presents a challenge in creating accurate status maps. Some ponds that have been abandoned or unused for a period may still legally be considered active, with the potential for fish production to resume. This can lead to misclassifications when detecting them as abandoned ponds using the proposed methodology, especially if they suddenly become operational again. Similarly, severe weather events can cause significant damage to ponds, which may require up to several years for repairs before operations can resume. These damaged ponds may also appear as abandoned but can still be legally active if owners or operators can demonstrate tangible signs of possession or operational activities. There are also instances where seemingly unused or abandoned ponds are later found to be operated by a particular entity or person who manages adjacent ponds, rendering them legally active and available for future use. To address these concerns, regular monitoring is recommended to track activities on these fishponds and provide a more accurate assessment of their actual status.

5. CONCLUSION

This study has successfully investigated the utilization of radar remote sensing, specifically Sentinel-1 SAR images, for mapping fishpond status. A preliminary methodology was developed, leading to promising outcomes. The research also demonstrated the potential of Sentinel-1 for accurately mapping active and abandoned fishponds, especially when inputs and insights from people familiar with the dynamics of fishpond operations are incorporated. However, the use of these datasets is recommended to be limited to larger fishponds due to their medium spatial resolution, which hampers their ability to effectively detect smaller ones. Nevertheless, the initial exploratory methodology offers valuable insights into the applicability of Sentinel-1 images, or radar images in general. Future enhancements to this methodology can be explored to address the identified limitations and challenges, making it more robust and precise, especially in classifying abandoned or disused ponds. The established workflow can also serve as a foundational methodology for broader-scale mapping and monitoring of fishponds with FLAs and their conditions nationwide, which the Bureau of Fisheries and Aquatic Resources (BFAR) could adopt and implement.

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