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Assessing spatiotemporal differences in shrimp ponds using remote sensing data and machine learning algorithms

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ADB Working Paper Series

**ASSESSING SPATIOTEMPORAL
DIFFERENCES IN SHRIMP PONDS
USING REMOTE SENSING DATA AND
MACHINE LEARNING ALGORITHMS**

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Abstract

Shrimp farming and exporting is the main income source for the southern coastal districts of the Mekong delta. Monitoring these shrimp ponds is helpful in identifying losses incurred due to natural calamities like floods, sources of water pollution by chemicals used in shrimp farming, and changes in the area of cultivation with an increase in demand for shrimp production. Satellite imagery, which is consistent with good spatial resolution and helpful in providing frequent information with temporal imagery, is a better solution for monitoring these shrimp ponds remotely for larger spatial extent. The shrimp ponds of Cai Doi Vam township, Ca Mau Province, Viet Nam were mapped using DMC-3 (TripleSat) and Jilin-1 high-resolution satellite imagery for the years of 2019 and 2022. The 3m spatial resolution shrimp pond extent product showed an overall accuracy of 87.5% with a producer's accuracy of 90.91% (errors of omission = 11.09%), and a user's accuracy of 90.91% (errors of commission = 11.09%) for the shrimp pond class. It was noted that 66 ha of shrimp ponds in 2019 were observed to be dry in 2022, and 39 ha of other ponds had been converted into shrimp ponds in 2022. The continuous monitoring of shrimp ponds helps achieve sustainable aquaculture and acts as crucial input for the decision-makers for any interventions.

Keywords: Jilin-1, Mekong delta, shrimp farming, sustainable aquaculture, TripleSat

JEL Classification: Q22, R12, Q01

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1. INTRODUCTION

Over the past three decades, aquaculture in Asia has produced more than 90% of the world's output and played significant roles in food security, poverty alleviation, employment, and overall economic development in many Asian countries. Aquaculture has been a long-standing custom in Asia, although it has only recently emerged, some four or five decades ago, as a major food production industry (Suzuki 2021). Shrimp farming in Viet Nam has been growing discernibly since the government passed a resolution in 2000 allowing the conversion of less productive rice land in coastal areas to aquaculture ponds (Dhar 2021). In terms of shrimp exports, Viet Nam was placed third in the world in 2019 with 13.6% of the market share, behind only India (15.7%) and Ecuador (14%) (Anderson, Valderrama, and Jory 2019). The shrimp production plan by the Ministry of Agriculture and Rural Development in Viet Nam predicted that the shrimp farming area would be 750,000 ha in 2022 and export turnover would be over USD4 billion, up 2.56% compared to 2021. Aquaculture, including shrimp ponds, is a large contributor to global food security and rural livelihoods and can also help preserve sustainable coastal environments (Abisha et al. 2022; Didar-UI Islam and Bhuiyan 2016; Lam et al. 2022; Parven et al. 2022; Shava and Gunhidzirai 2017).

In Viet Nam, the Mekong delta, with 12% of Viet Nam's total area, has 67% of water bodies, including fresh and brackish water bodies other than rivers (Loc et al. 2021). But now, in Ca Mau Province, coastal aquaculture faces a rapid shift with increasing production and intensive shrimp culture, resulting in poor water quality and frequent occurrence of disease outbreaks (Suzuki and Hoang Nam 2018).

Various studies in the Mekong delta focus on sustainable aquaculture development and the combined farming system of agriculture and aquaculture (Tenório et al. 2015; Wilder and Phuong 2002). Many sustainable issues concern water quality due to chemical usage in shrimp cultivation (Braun et al. 2019; Lee, Suzuki, and Vu 2019; Sebesvari et al. 2012; Suzuki and Nam 2022; Tan, Tran, and Loc 2020). Certain studies are related to climate change impacts on agriculture and the aquaculture sector (Leigh et al. 2020). Despite these many studies based on statistics and farmer interviews, very few EO-based monitoring systems have been developed for shrimp ponds (Gentry et al. 2017), and most studies carried out have been related to changes in mangrove areas (Bèland et al. 2006; Gusmawati et al. 2016). Monitoring aquaculture products has shifted to relying heavily on remote sensing technology due to its advantages in estimating area under cultivation and real-time monitoring of ponds (Cui et al. 2019; Hou et al. 2022; MacAulay et al. 2022; Ottinger, Clauss, and Kuenzer 2017; Seto and Fragkias 2007). Flood detection, along with wetlands and water bodies' identification play a major role in contributing to aquaculture mapping (M. Gumma et al. 2009; M. K. Gumma et al. 2019). Many studies have generated and used water-based indices (Feyisa et al. 2014; M. K. Gumma et al. 2019; Li et al. 2022) to identify water bodies with a variety of satellite imagery ranging from moderate (MODIS) to high (Sentinel) spatial resolution. Previously many aquaculture mapping studies were based on open-source satellite imagery, such as Landsat, and analyses based on Sentinel imagery with more spectral bands but with a lower spatial resolution were also carried out (Diniz et al. 2021; Kurekin et al. 2022; Sun et al. 2020; Virdis 2014), in addition to time series analysis (Ottinger et al. 2021). Recently, many water bodies and aquaculture mapping studies, particularly on a global scale, have been conducted using a cloud platform, especially Google Earth Engine (B. Chen et al. 2017; Farda 2017; Giri et al. 2022; Hardy, Oakes, and Ettritch 2020; Kolli et al. 2022; Wang et al. 2020). Since the study area is very highly dominated by water bodies that include ponds and major and minor streams, approaches such as segmentation (Peralta and

Tamondong 2015) and deep learning-based methodologies alone cannot classify the variations created by newly developing minor ponds (Islam et al. 2008; Lacaux et al. 2007; Prasad et al. 2019). In order to differentiate water bodies, very high spatial resolution data are needed. This study utilized very high-resolution data (~3 m) and adopted machine learning algorithms as well as vectorization for classifying variations in water bodies to identify shrimp ponds.

Many Asian nations have not yet fully adopted good aquaculture governance. The rapid growth in the aquaculture sector has given rise to some of the most difficult sustainability problems, including inefficient resource use, detrimental environmental effects, frequent disease outbreaks, and food safety threats, which in turn limit the sector's potential to grow sustainably in the future. Monitoring shrimp ponds using EO data could be useful in grasping a firm understanding of the current situation of the aquaculture sector to meet the increased demand for aquatic food and sustain aquaculture's much-needed expansion.

The primary objectives of this research are thus the development of a system for the regional-level mapping of coastal pond aquaculture for the Cai Doi Vam Township, Phu Tan District, Ca Mau Province, based on high spatial resolution single-date satellite imagery and ground truth data, as well as assessment of the accuracy and analysis of aquaculture areas.

2. DATA

2.1 Study Area

This study focused on the Cai Doi Vam Township, Phu Tan District, a rural district of Ca Mau Province in the southern coastal zone of the Mekong delta region of Viet Nam (Figure 1), which lies at 8°52'N and 104°49'E.

Phu Tan District has a total area of 46,433 ha, with all the areas being affected by the saline intrusion, which also applies to the Cai Doi Vam Subdistrict (ADB 2013). This area is highly dominated by shrimp and other ponds.

2.2 Satellite Data

The detection of even minute linear structural elements in small-scale pond aquaculture structures with a size of less than 1 hectare is only achievable with high-resolution imagery. The analysis was based on optical data gathered from a high-resolution geometric (DMC-3) sensor imaging with a spatial resolution of 3.2 m from TripleSat on 4 March 2019. Jilin satellite images for 2022 were collected on a different single date and had a comparable spatial resolution (2.88 m of MS).

Pan-sharpening with image data fusion and image enhancements were applied based on linear stretches, and mosaicking was carried out on georeferenced data sets. The three bands were NIR, red, and green color chosen for a composite FCC, as shown in Figure 1. The bands and their spatial characteristics of satellite imagery and the utilization of different satellite imagery in the study are as shown in Table 1. Single-date TripleSat and Jilin imagery and temporal Sentinel-2 imagery are used for the study.

Figure 1: Cai Doi Vam Subdistrict of Phu Tan District, Ca Mau Province Viet Nam Study Area

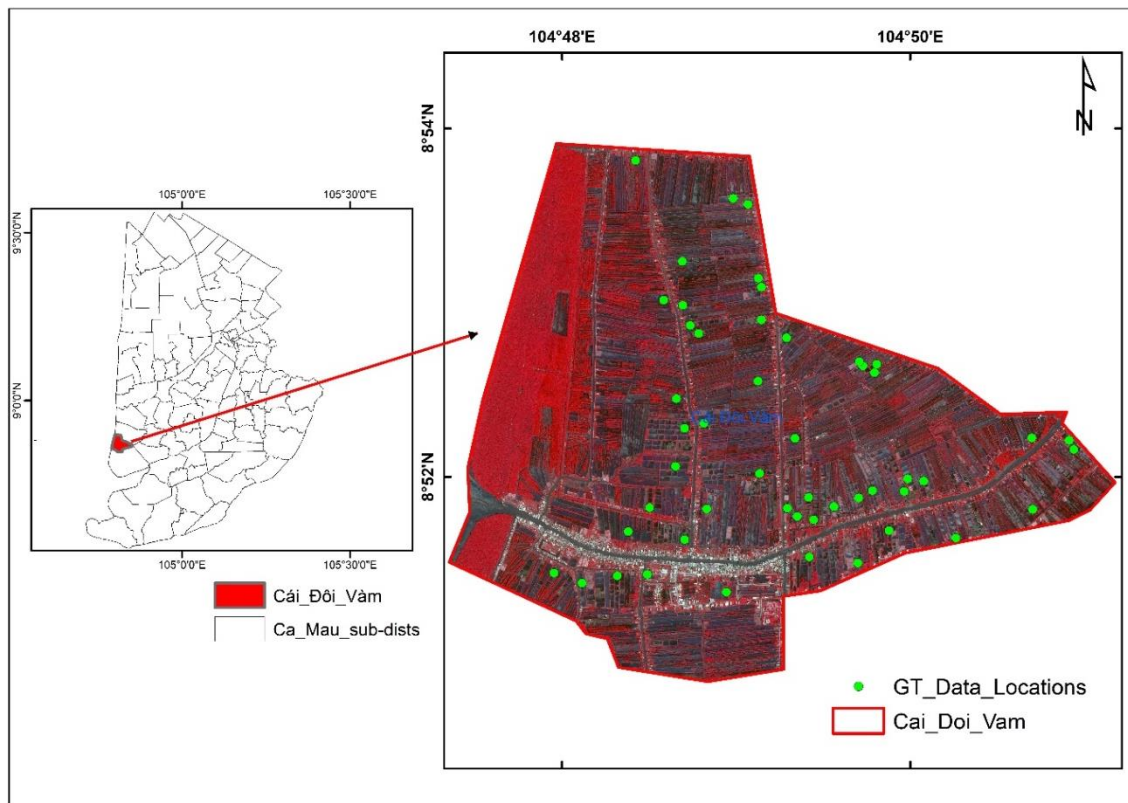


Table 1: Satellite Data with their Characteristics and Specific Utilization

| Satellite | Bands – Spatial Resolution | Bands | Utilization |
|-----------------|-------------------------------------|-------------------------------|---|
| DMC-3/TripleSat | Pan: 0.8 m, Multispectral: 3.2m | Pan, Blue, Green, Red, NIR | 2019 Shrimp Ponds Map |
| Jilin-1KF01A | Pan: 0.75 m, Multispectral: 3m | Pan, Blue, Green, Red, NIR | 2022 Shrimp Ponds Map |
| Sentinel-2 | B2, B3, B8: 10 m, B11, B12: 20 m | B1–B8, B8a, B9–B12 | Water Bodies Mask (through different water indices) |

2.3 Ground Survey Data

We also utilized GIS data on the location of shrimp ponds, which were collected from about 600 farmers in Phu Tan District during a household survey. Out of these, 45 sample shrimp pond points are observed within the study area of Cai Doi Vam.

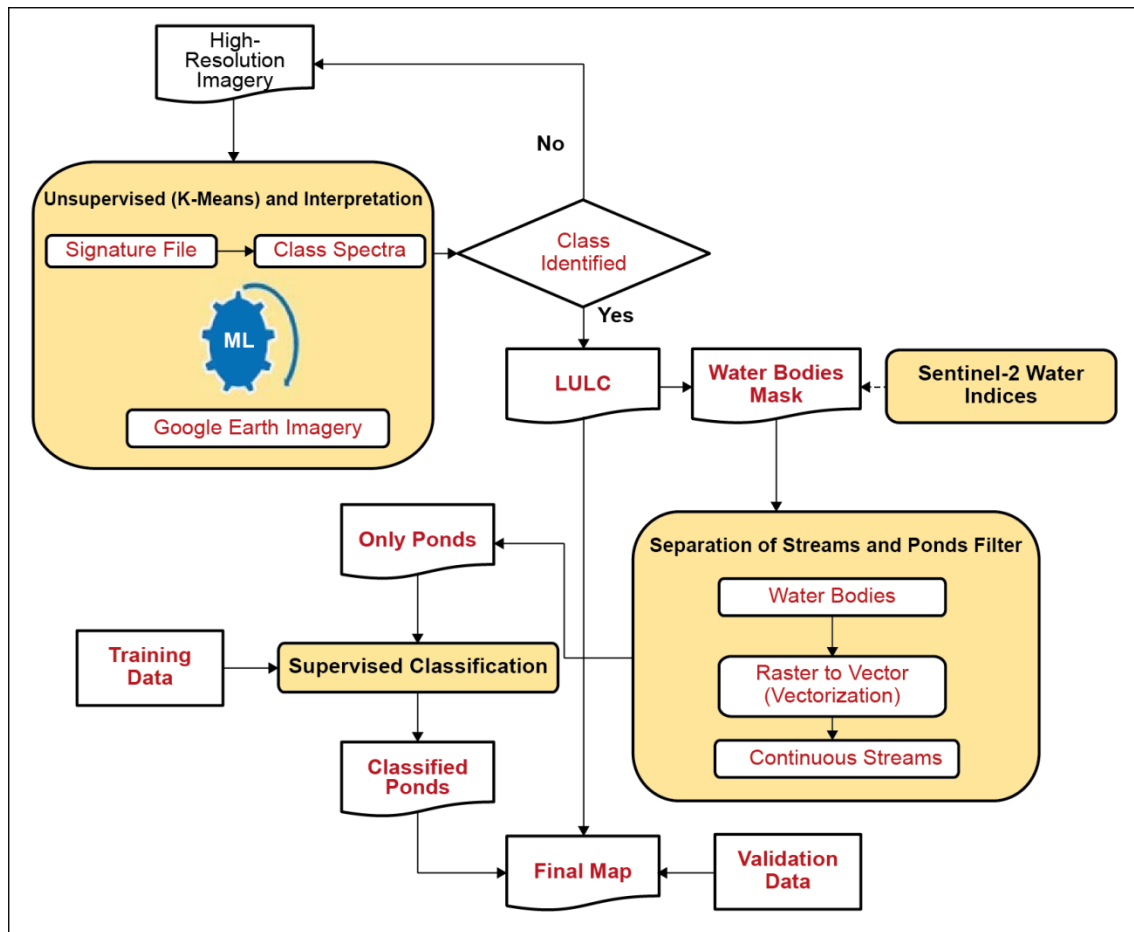
3. METHODS AND APPROACHES

3.1 Wetlands and Land Use Mapping

The land use and land cover with the shrimp class were mapped using DMC-3 data for 2019 while the same was mapped using Jilin data for 2022 with the help of unsupervised classification (Teluguntla et al. 2017; Thenkabail et al. 2007). An accuracy assessment was performed with validation data. Spatial analysis was used

to create spatial products with a greater resolution of 3 m that recorded changes effectively (Figure 2).

Figure 2: The Methodology Used to Map Shrimp Ponds Using High Spatial Resolution Data



Primarily unsupervised classification was done targeting the LULC of the study area and potential shrimp ponds that can be identified. Satellite imagery was classified using ISO CLASS cluster K-means unsupervised classification with a convergence value of 0.99 and 20 iterations, yielding 20 classes followed by successive generalization. These classes were identified using visual interpretation from Google Earth imagery. There is an opportunity to observe temporal changes in the study region using Google Earth imagery. We further used Sentinel-2-based various water indices to create a water bodies mask. NDWI, MDWI, AWEI_{nsh}, AWEI_{sh}, and WRI indices were computed to identify ponds and other wetlands. This is to overcome the limitation due to single-date cloud cover imagery. We set a conservative threshold beyond which we would exclude aquaculture development. This led to the exclusion of various classes, such as built-up areas and other LULC, and in rare instances, this may have also included shrimp ponds. If any gaps arise in any class, this class can be reclassified, and an initial classification map will be prepared, which will be used in secondary supervised classification.

3.2 Separation of Streams Using LULC Vectorization

Wetlands and water bodies classes for the 2019 and 2022 cropping years were separated. Vectorization was applied to the water bodies to identify stream networks. Naturally developed stream networks and created aquaculture ponds can be distinguished from one another by the compact geometries of the streams. A water bodies masked raster was used for supervised classification with training points.

3.3 Supervised Classification of Ponds to Separate Shrimp Ponds

This study employed the supervised classification approach by using maximum likelihood classification. The training samples for other ponds and water bodies were selected from Google Earth images and field survey data. The total number of training samples selected was 45 for shrimp ponds and 25 for other ponds. A minimum of 70 pixels was ensured for each sample to guarantee accuracy.

3.4 Accuracy Assessment

A total of 56 stratified, randomly distributed validation samples were used to determine the accuracy of Cai Doi Vam's final shrimp ponds map and overall accuracies (Russell G Congalton and Green 2019). The columns of an error matrix contain the ground survey data points, and the rows represent the results of the classified crop maps (Russell G. Congalton 1991). A frequently used measure is Kappa (Cohen 1960), representing the agreement among users and reference ground survey data.

4. RESULTS AND DISCUSSION

4.1 Spatial Distribution of LULC

Sentinel-2-based water indices, which are helpful in overcoming mixed classification or missed water pixels in single imagery, are used in developing binary water masks to separate pond water from the land around it. But in Sentinel-2-based water indices, shrimp ponds do not have clear boundaries due to its spatial resolution. Indices like MNDWI and AWEI, in particular, utilize the SWIR band, which is even coarser than other visible bands, in their calculation (Figure 3).

After initial unsupervised classification for the LULC of the study area, it is observed that shrimp ponds are well connected or situated near a stream network. Ponds are very closely situated in built-up areas and bunds are mostly covered by vegetation. Other ponds are structures with mangroves situated inside the ponds or abandoned ponds. Preliminary LULC maps of both years are shown in Figure 4. There is a clear reduction in water bodies and other LULC compared to vegetation. This is due to the growth of mangroves and flora in ponds, as well as the fact that barren land and dry soil are now covered by vegetation. This decrease in water bodies suggests a decrease in the areas used for aquaculture; however, a comprehensive change detection analysis will be available after distinguishing these water bodies.

Figure 3: Sentinel-2 Water Indices a. NDWI, b. MNDWI, c. WRI, d. $AWEI_{nsh}$, e. $AWEI_{sh}$ Based Water Bodies Masks

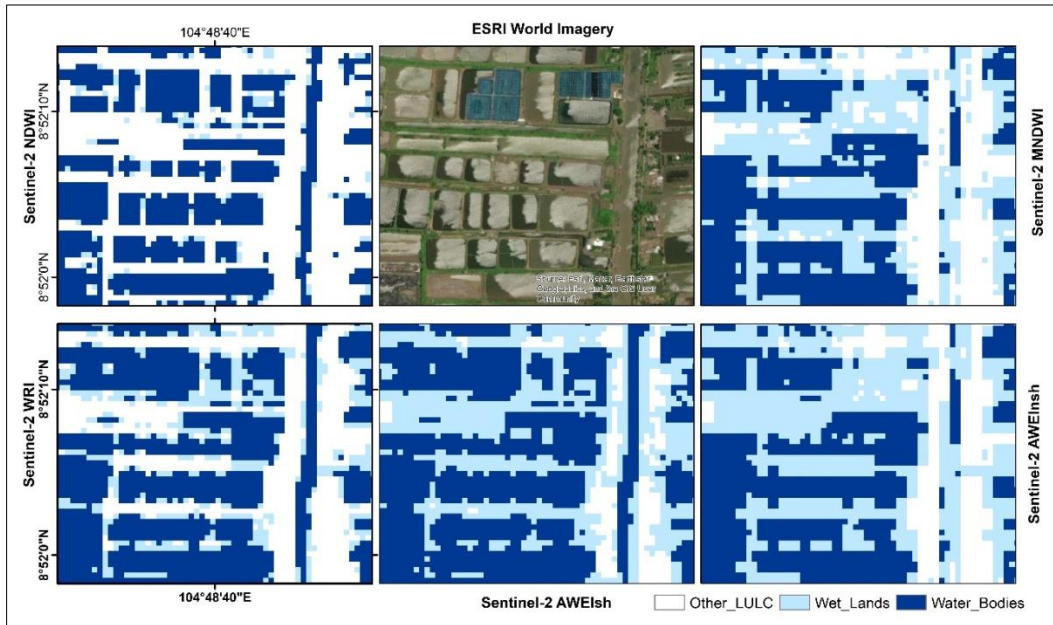
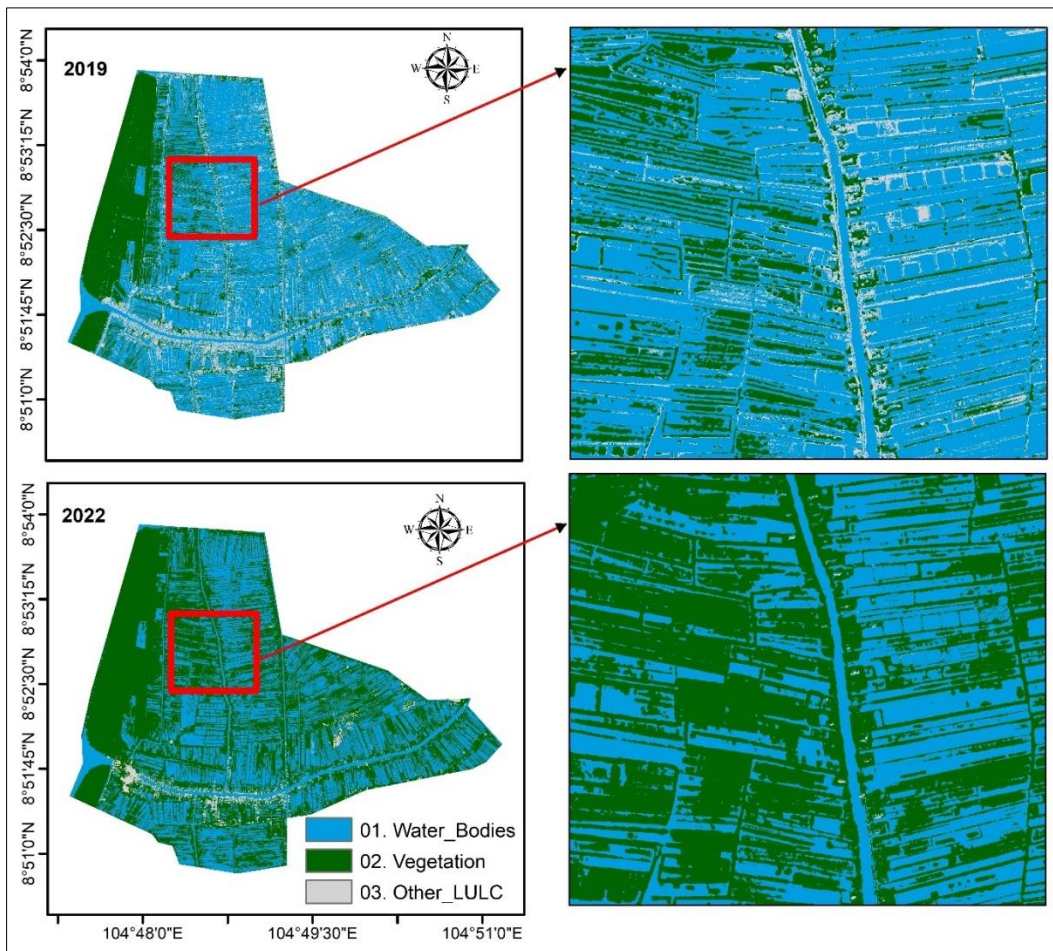


Figure 4: LULC Map of Cai Doi Vam for 2019 and 2022 with Enlarged View

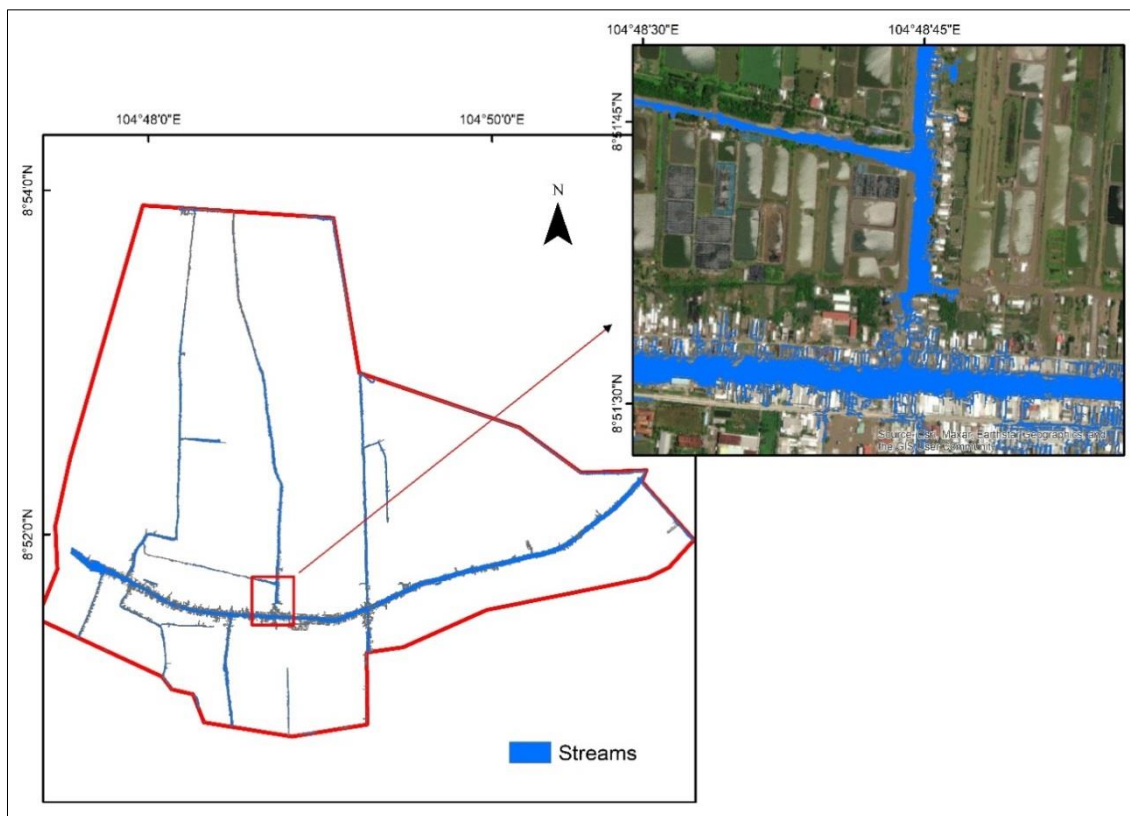


But due to common characteristics of water bodies and similar pixel values we obtained mixed classes of shrimp ponds, other ponds, and stream networks. To eliminate these water bodies, classes were separated after unsupervised classification using vectorization utilizing the unique structure of stream networks.

4.2 Streams Vectorization

The water bodies class (raster) obtained from the initial classification was converted into a vector format. With the help of vectorization of water bodies, streams were identified using their structure as shown in Figure 5. These stream network identifications are helpful in separating ponds and also in monitoring shrimp pond waste disposal methods and the quality of wastewater.

Figure 5: Stream Network Map with an Enlarged View over Satellite Imagery



4.3 Spatial Distribution of Shrimp Ponds/Fishponds

The shrimp pond maps were prepared using 3 m resolution for the years 2019 and 2022 (Figures 6 and 7). Shrimp ponds, other ponds, streams, and other LULC were delineated. Targeted classes like shrimp ponds, other ponds, and streams were classified with better accuracy than the other classes because of the spectral resolution of the imagery, which is a tradeoff when classifying very high-resolution imagery. Built-up and other LULC were provided as a single class in the Final Maps. Other LULC classes include barren land along with embankments of ponds for the case of 2019, while in 2022 these are covered by vegetation. The stream network consists only of major water supply channels, and it does not include those micro-channels contributing to individual ponds. Changes in shrimp pond structures were clearly seen within the

enlarged area itself, i.e., the conversion of larger ponds into a number of smaller ponds (within the enlarged view we can see two long ponds converted into eight smaller ponds) as well as the increased total number of shrimp ponds.

The Cai Doi Canal is home to the majority of shrimp ponds. A more thorough investigation of each class's change can be seen in the final maps of shrimp ponds (Figure 6 and Figure 7).

Between 2019 and 2022, an area of 26 ha of shrimp ponds (15%), 337 ha of other ponds (33%), and 42 ha of streams diminished or dried out. This change, on the other hand, was concealed by vegetation, as 650 ha of land cover increased in vegetation class, which is nearly equivalent to the area lost under water bodies. It has been observed that the vegetation-covered area increased by about 115% in 2022 compared to 2019, whereas other land uses, like shrimp ponds, other ponds, and other LULC, showed declines (Table 2).

Figure 6: a. Shrimp Pond Map of 2019 Based on DMC-3, b. Enlarged View of Classified Ponds, c. Enlarged View of Satellite Imagery

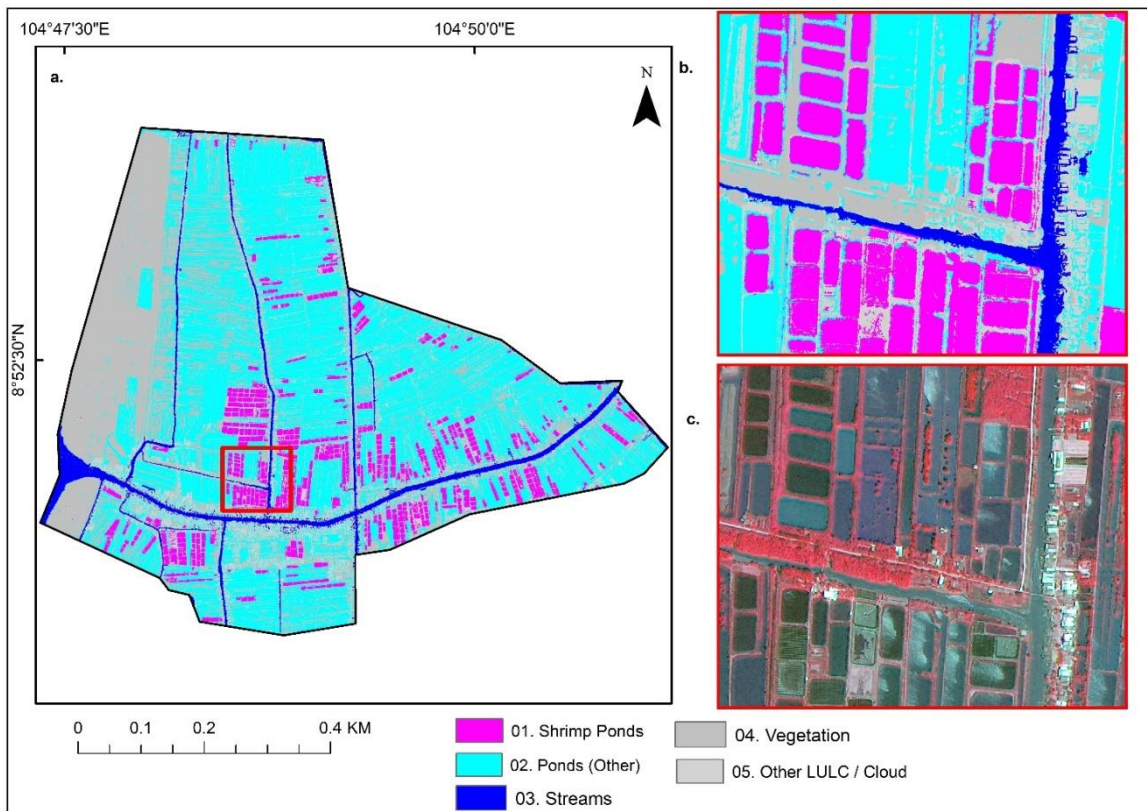


Figure 7: a. Shrimp Pond Map of 2022 Based on Jilin, b. Enlarged View of Classified Ponds, c. Enlarged View of Satellite Imagery

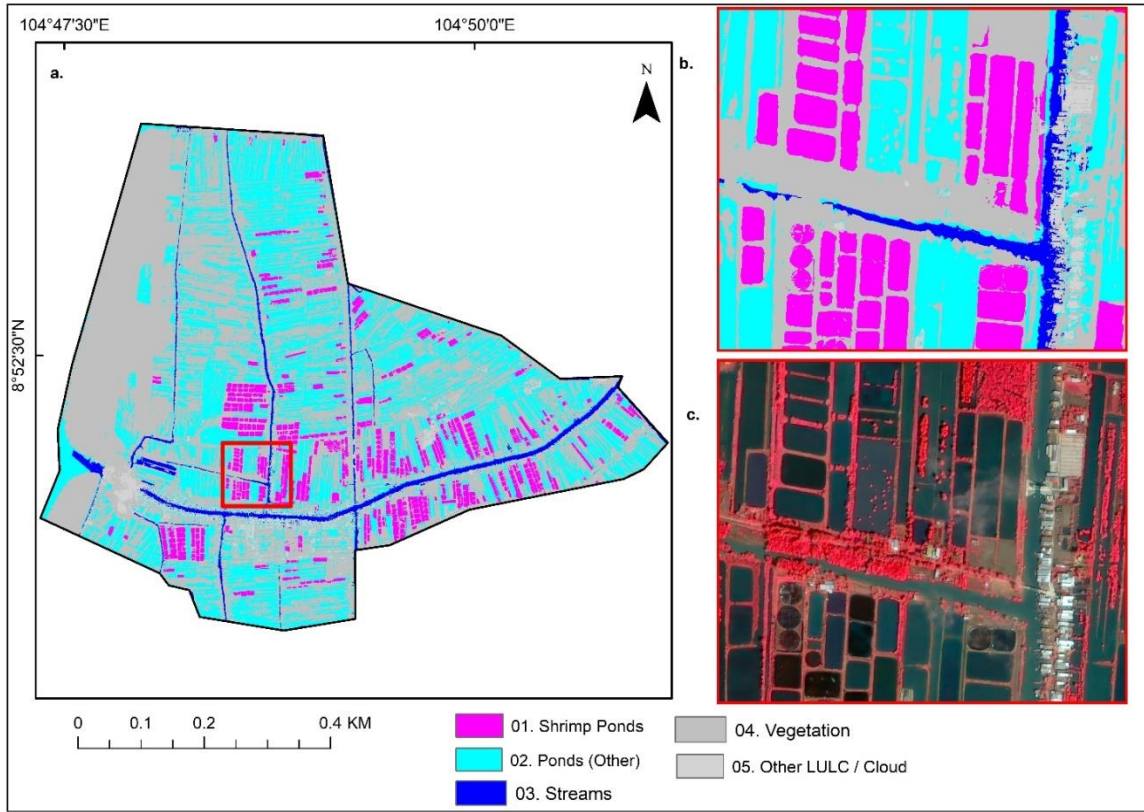


Table 2: LULC Change Statistics from 2019 to 2022

| LULC | 2022 (ha) | 2019 (ha) | Change (ha) | % Change |
|-----------------|-----------|-----------|-------------|----------|
| 01_Shrimp_Ponds | 148.11 | 174.71 | -26.60 | -15.20 |
| 02_Other_Ponds | 682.51 | 1,020.01 | -337.50 | -33.08 |
| 03_Streams | 67.48 | 109.56 | -42.08 | -38.40 |
| 04_Vegetation | 1,210.77 | 560.67 | 650.10 | 115.95 |
| 05_Other_LULC | 55.09 | 299.08 | -243.99 | -81.58 |

4.4 Accuracy Assessment

The accuracy assessment of the shrimp pond classification for 2019 was 87% accurate overall. Targeted shrimp ponds had 90% accuracy. Dried clay soil and bunds around ponds were classified as built-up areas. An error matrix (Table 1) was generated for Cai Doi Vam providing producers, users, and overall accuracies.

Table 3 shows the accuracy assessment of 2022 shrimp pond classification with the same 56 sample points used for accuracy assessment. An overall accuracy of 89% was obtained because the cloud cover was mostly in other LULC and the vegetation area was mixed with cloud cover. But the targeted shrimp ponds have more than 90% accuracy as do those misclassified were as other ponds.

Table 3: Overall Accuracy with Producers' and Users' Accuracy and Kappa Coefficient for 2019 and 2022

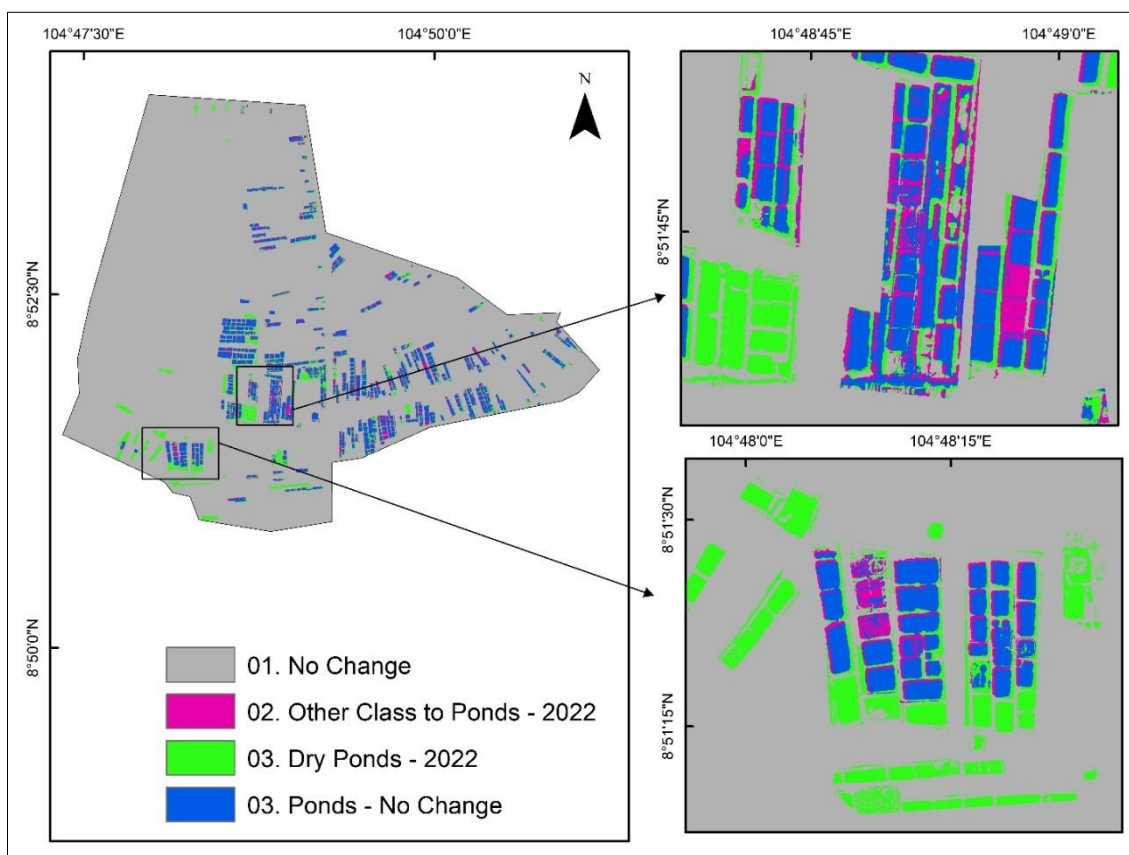
| LULC Class | Reference Totals | Classified Totals | Number Correct | Producers' Accuracy (%) | Users' Accuracy (%) | Kappa Coefficient |
|---------------------------------|------------------|-------------------|----------------|-------------------------|---------------------|-------------------|
| a. 2019 | | | | | | |
| 01. Shrimp Ponds | 11 | 11 | 10 | 90.91 | 90.91 | 0.8255 |
| 02. Ponds (Other) | 22 | 26 | 22 | 100.00 | 84.62 | |
| 03. Streams | 7 | 6 | 6 | 85.71 | 100.00 | |
| 04. Vegetation | 14 | 11 | 11 | 78.57 | 100.00 | |
| 05. Other LULC | 2 | 0 | 0 | | | |
| Totals | 56 | 56 | 49 | | | |
| Overall Classification Accuracy | | | | | 87.50 | |
| b. 2022 | | | | | | |
| 01. Shrimp Pond | 10 | 9 | 9 | 90.00 | 100.00 | 0.8531 |
| 02. Ponds (Other) | 21 | 20 | 18 | 85.71 | 90.00 | |
| 03. Streams | 6 | 5 | 5 | 83.33 | 100.00 | |
| 04. Vegetation | 16 | 19 | 16 | 100.00 | 84.21 | |
| 05. Other LULC | 2 | 1 | 1 | 50.00 | 100.00 | |
| Totals | 56 | 56 | 50 | | | |
| Overall Classification Accuracy | | | | | 89.29 | |

4.5 Change Detection in Shrimp Ponds

TripleSat and Jilin data helped in identifying shrimp ponds with up to 90% accuracy, but in order to achieve this high level of accuracy, the cloud cover has to be low. Change detection was carried out for these shrimp ponds for the two different years, and it was identified that 639 ha of shrimp ponds were left dry in 2022 for the entire Phu Tan District, of which 66 ha were in Cai Doi Vam Subdistrict itself (Figure 8). Further, 39 ha of other ponds in 2019 were converted into shrimp ponds in 2022.

Aquaculture has tremendous potential to assist with global food security, making the prediction of pond production volumes a crucial research goal for the coming years. Quantitative data on aquaculture production at both the national and subnational levels are accessible but typically with a lack of precision. In this study, we compiled annual statistics for two years on aquaculture productivity, focusing mostly on shrimp ponds.

Figure 8: Change of Shrimp Ponds from 2019 to 2022



4.6 Discussion on Monitoring Shrimp Ponds Using RS Technology

It is challenging to identify individual ponds from the mixed pixels in the 30 m or 10 m spatial resolution satellite images, and this is why this study focuses on the extraction of aquaculture ponds from high spatial resolution imagery for mapping (Duan et al. 2021; Ottinger, Clauss, and Kuenzer 2018; Prasad et al. 2019). It is challenging to use conventional classification techniques or a single spectral index to effectively classify the aquaculture ponds because these ponds are also a sort of water body split by embankments into a large network of smaller ponds (Alexandridis et al. 2008; Xia, Guo, and Chen 2020). By combining spectral data, spatial features, and structural features, we were able to build a system that would let the smaller aquaculture ponds be taken out on a regional scale. Water bodies are typically extracted via spectral index construction, and there are a variety of such indices. The best known are NDWI, MNDWI, WRI, and AWEI (including $AWEI_{sh}$ and $AWEI_{Insh}$) (Veetil, Quang, and Trang 2019). Shrimp ponds mapped using single-date imagery for the two different time periods of 2019 and 2022 provide us with valuable information on the changes in shrimp cultivation. We observed an overall decrease in the area under shrimp ponds over these two years. The use of remote sensing technology to monitor changes in the size and number of ponds and frequent mapping using EO data enable us to have reliable data to predict the production volume in one area ahead of time. This kind of information is valuable for buyers and processors as they can adjust their exporting volume or arrange other procurement channels to cover the loss when a decrease in production is predicted. This information is also helpful in policymaking towards

sustainable production for future years (Y. Chen et al. 2021). For example, the government or international organizations can monitor whether the coastal areas have been developed for aquaculture use illegally, and if so, to what extent.

We also note that change detection studies with this imagery have limitations: DMC-3/TripleSat has low cloud coverage; however, it also has a slightly lower spatial resolution than Jilin. Further, Jilin-1's overall accuracy was 2% higher than that of DMC-3/TripleSat because of comparatively greater spatial resolution. This high resolution enabled us to extract even smaller shrimp ponds very clearly, compared to what we can do with the Sentinel imagery.

5. CONCLUSION

As Jilin and DMC-3 satellite data are optical data vulnerable to cloud cover, this hampers the availability of data on cloudy days, especially during rainy seasons. This also results in more mixed classes. Time series imagery can help in enhancing classification accuracy (in classifying vegetation and water bodies). The categorization may benefit from necessary field-based observations (particularly features to distinguish between shrimp ponds and other ponds). There is a high possibility of mixed classes while differentiating water bodies because the area is dominated by water. Some water bodies have vegetation and water waves, causing a change in reflectance values leading to misclassification. TripleSat and Jilin were not helpful in built-up and settlement classification due to the absence of the SWIR band.

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