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Article

Mapping Shrimp Pond Dynamics: A Spatiotemporal Study Using Remote Sensing Data and Machine Learning

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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 a 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 2019 and 2022. The 3 m 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

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1. Introduction

Over the past 3 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 [1]. 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 [2]. In terms of shrimp exports, Viet Nam placed third in the world in 2019, with 13.6% of the market share, behind only India (15.7%) and Ecuador (14%) [3]. 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 USD 4 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 [4–8].

In Viet Nam, the Mekong Delta contains 67% of the country's total water bodies, including fresh and brackish water bodies other than rivers, whereas the land area is only 12% of the total area [9]. In Ca Mau Province, coastal aquaculture faces a rapid shift, with increasing production and intensive shrimp culture resulting in poor water quality [10].

Various studies in the Mekong Delta focus on sustainable aquaculture development and the combined farming system of agriculture and aquaculture [11,12]. Many sustainable issues concern water quality due to chemical usage in shrimp cultivation [13–17]. Certain studies are related to climate change impacts on agriculture and the aquaculture sector [18]. Despite these many studies based on statistics and farmer interviews, very few EO-based monitoring systems have been developed for shrimp ponds [19], and most studies carried out have been related to changes in mangrove areas [20,21]. Monitoring aquaculture products has shifted to relying heavily on remote sensing technology due to its advantages in estimating the area under cultivation and real-time monitoring of ponds [22–26]. Flood detection, along with wetlands and water bodies identification, play a major role in contributing to aquaculture mapping [27,28]. Many studies have generated and used water-based indices [27,29,30] to identify water bodies with a variety of satellite imagery ranging from moderate (MODIS) to high (Sentinel) spatial resolution [31]. 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 lower spatial resolution were also carried out [32–35], in addition to time series analysis [36,37]. Recently, many water bodies and aquaculture mapping studies, particularly on a global scale, have been conducted using a cloud platform, especially Google Earth Engine [38–43]. Since the study area is very highly dominated by water bodies that include ponds and major and minor streams, approaches such as segmentation [44] and deep learning-based methodologies alone cannot classify the variations created by newly developing minor ponds [45–47]. 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. The study area is highly vulnerable to natural disasters like floods, droughts, and coastal erosion. The time period under investigation is from 2019 to 2022, during which extensive shoreline erosion was observed in the region. Ca Mau province was particularly affected, with an erosion rate of 32.5 m/year observed in the east and −12.9 m/year in the west after five years. There is a complex climatic context in the study area; according to the Vietnam Meteorological and Hydrological Administration, the region experienced a higher number of typhoons and tropical depressions than in previous years. These weather events were associated with increased rainfall and storm surges, which likely contributed to the observed coastal erosion [48,49].

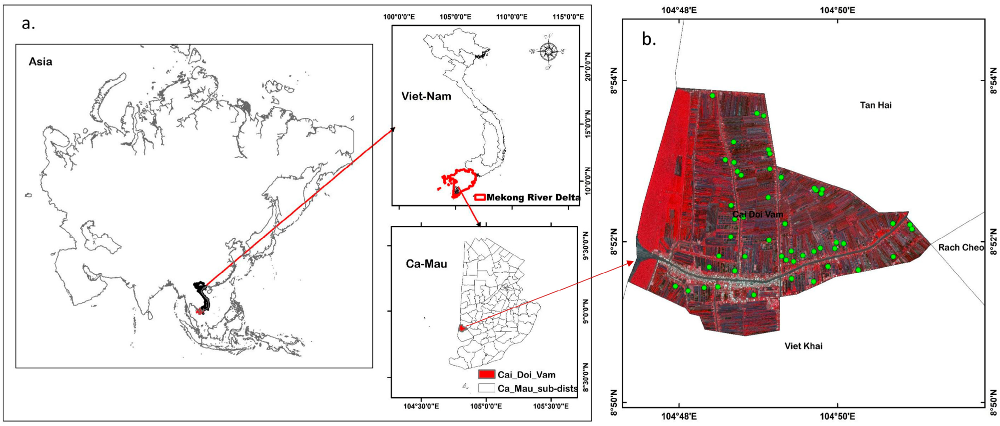

Figure 1. (**a**) Location of the Study Area Cai Doi Vam Subdistrict of Phu Tan District, Ca Mau Province of Viet Nam in Asia. (**b**) The Detailed View of the Study Area and Neighboring Area represented with satellite data of DMC3 (Triplesat) in March of 2019 in FCC of NIR, Red, and Green.

Vietnam has experienced a warming trend over the past few decades, with an increase in average temperature of 0.5 °C per decade. This warming trend is projected to continue, with potentially significant impacts on the region's hydrology, including changes in precipitation patterns and sea level rise. The hydrology of the Cai Doi Vam area is complex, with a range of natural factors contributing to coastal erosion. These factors include the tidal regime, flow velocity and direction, wave height and direction to shore, and sediment volume [50,51].

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 Sub-district [52]. This area is highly dominated by shrimp and other ponds.

2.2. Satellite Data

The detection of small-scale pond aquaculture structures with a size of less than 1 hectare is only achievable with high-resolution imagery. The analysis was carried out based on optical high-resolution geometric (DMC3) 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 was applied based on linear stretches, and mosaicking was carried out on georeferenced datasets. 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 shown in Table 1. Single-date TripleSat and Jilin imagery and temporal Sentinel-2 imagery were used for the study.

Table 1. Satellite data with their characteristics and specific utilization.

Satellite	Bands—Spatial Resolution	Bands	Utilization
DMC3/TripleSat	Pan:0.8 m, Multispectral: 3.2 m	Pan, Blue, Green, Red, NIR	2019 Shrimp ponds Map
Jilin-1KF01A	Pan: 0.75 m, Multispectral: 3 m	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

Around 500 sample points related to shrimp cultivation and other LULC were collected across Phu Tan District. Out of the collected samples, 45 sample shrimp pond points were observed within the study area of Cai Doi Vam.

Data was collected during 15–22 October 2022 (Figure 1) using high spatial resolution google earth imagery on the following: (a) Location coordinates; (b) water bodies; (c) fishponds and shrimp ponds; (d) wetlands; and (e) settlements; (f) land cover categories (for example, trees, shrubs, grasses, and hills); (g) Documenting the landscape using, high spatial resolution google earth imagery. The purpose of this exercise was to identify different water body classes accurately during the classification process and assess the accuracy of the final maps.

3. Methods and Approaches

3.1. Wetlands and Land Use Mapping

The land use and land cover with the shrimp class were mapped using DMC3 data for 2019, while the same was mapped using Jilin data for 2022 with the help of unsupervised classification [53,54]. 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).

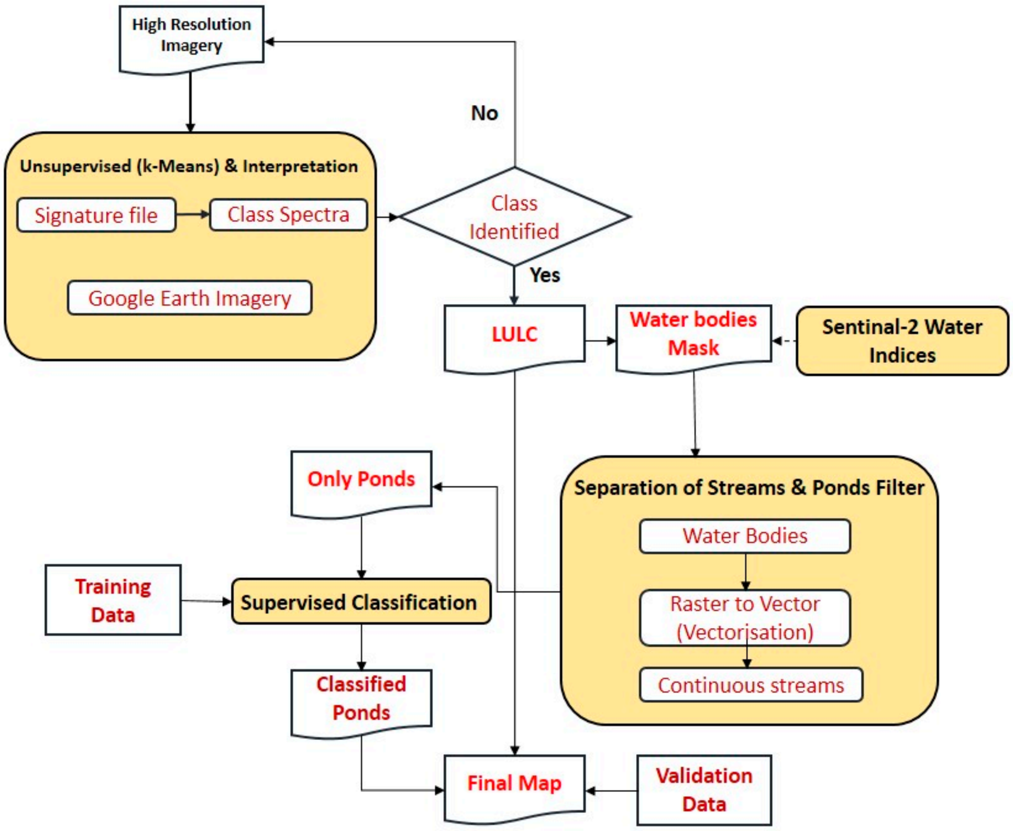

Figure 2. The methodology used to map shrimp ponds using high spatial resolution data.

The primarily unsupervised classification was conducted 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, AWEInsh, AWEIsh, and WRI indices were computed to identify ponds and other wetlands. Computation of various water indices, including NDWI (Normalized Difference Water Index), MNDWI (Modified Normalized Difference Water Index), AWEInsh (Automated Water Extraction Index), AWEIsh (Automated Water Extraction Index with shadows), and WRI (Water Ratio Index) was applied to Sentinel-2 imagery for effective mapping and monitoring of water bodies using the following equations:

$$\text{NDWI} = (\text{NIR} - \text{Green})/(\text{NIR} + \text{Green})$$

$$\text{MNDWI} = (\text{Green} - \text{SWIR})/(\text{Green} + \text{SWIR})$$

$$\text{AWEInsh} = 4 \times (\text{Green} - \text{SWIR}) - (0.25 \times \text{NIR} + 2.75 \times \text{SWIR})$$

$$\text{AWEIsh} = 4 \times (\text{Green} - \text{SWIR}) - (0.25 \times \text{NIR} + 2.75 \times \text{SWIR}) - (2.5 \times \text{Blue})$$

$$\text{WRI} = \text{Green}/\text{Red}$$

where:

"NIR" is the reflectance in the near-infrared band.
"Red" is the reflectance in the red band.
"Green" is the reflectance in the green band.
"Blue" is the reflectance in the blue band.
"SWIR" is the reflectance in the shortwave infrared band.

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 using ERDAS. 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 [55]. The columns of an error matrix contain the ground survey data points, and the rows represent the results of the classified crop maps [56]. A frequently used measure is Kappa [57], representing the agreement among users and producers regarding accuracy from 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 their spatial resolution. Indices like MNDWI and AWEI, in particular, utilize the SWIR band, which is even coarser compared to other visible bands in their calculation (Figure 3).

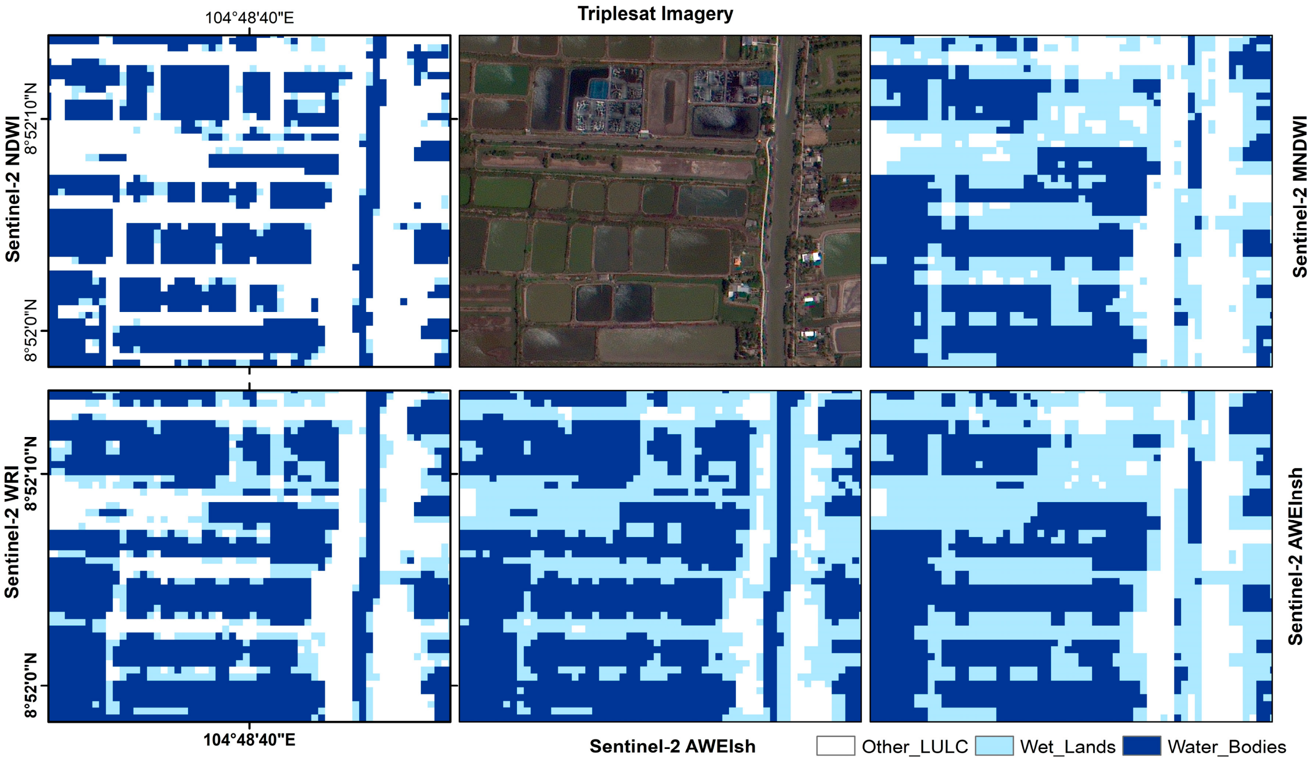

Figure 3. Sentinal-2 water indices NDWI, MNDWI, WRI, AWEInsh, AWEIsh base water bodies masks.

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.

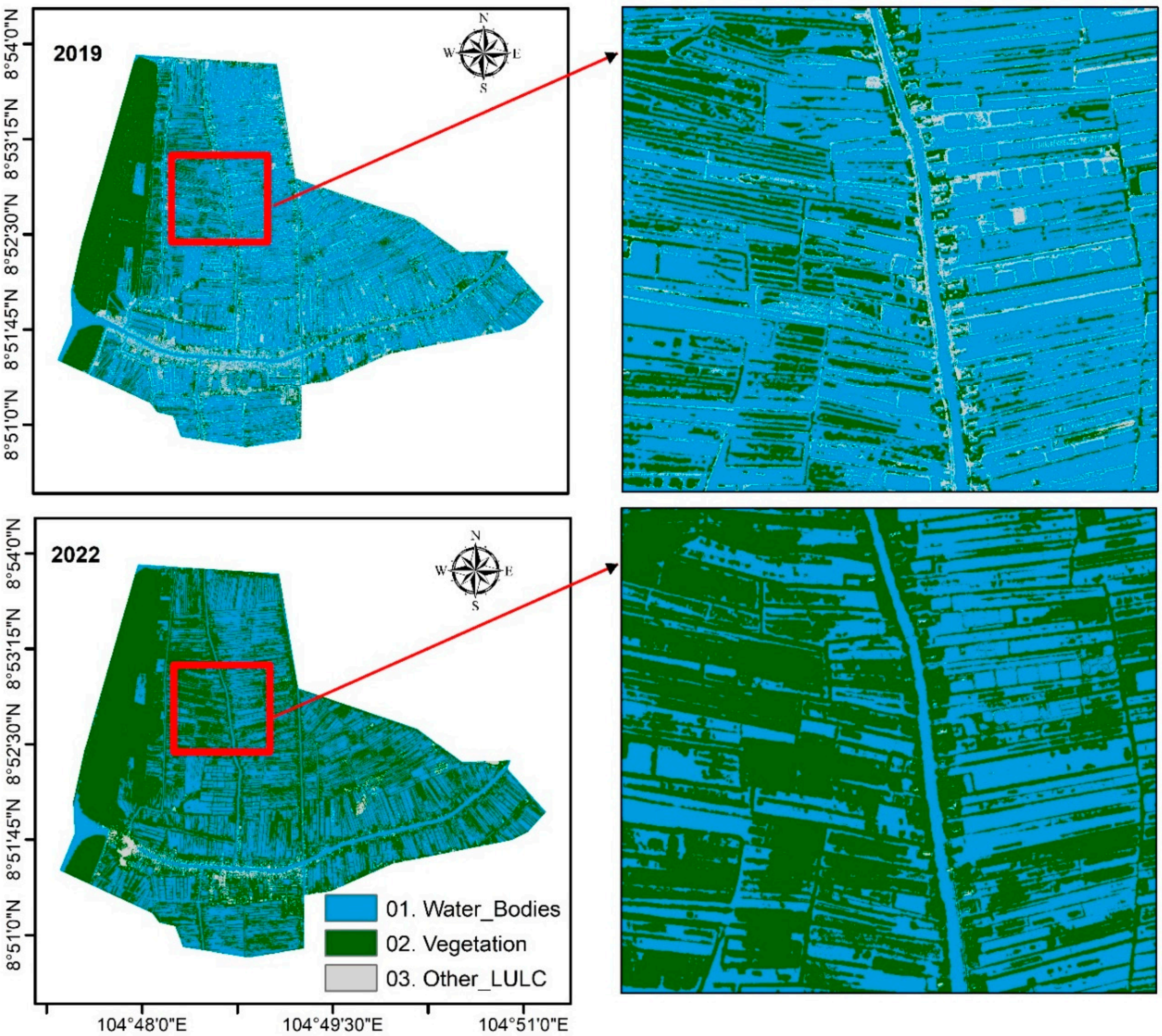

Figure 4. LULC Map of Cai Doi Vam for 2019 and 2022 with enlarged view.

But due to the common characteristics of water bodies and similar pixel values, they resulted in 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 vectors. With the help of the 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.

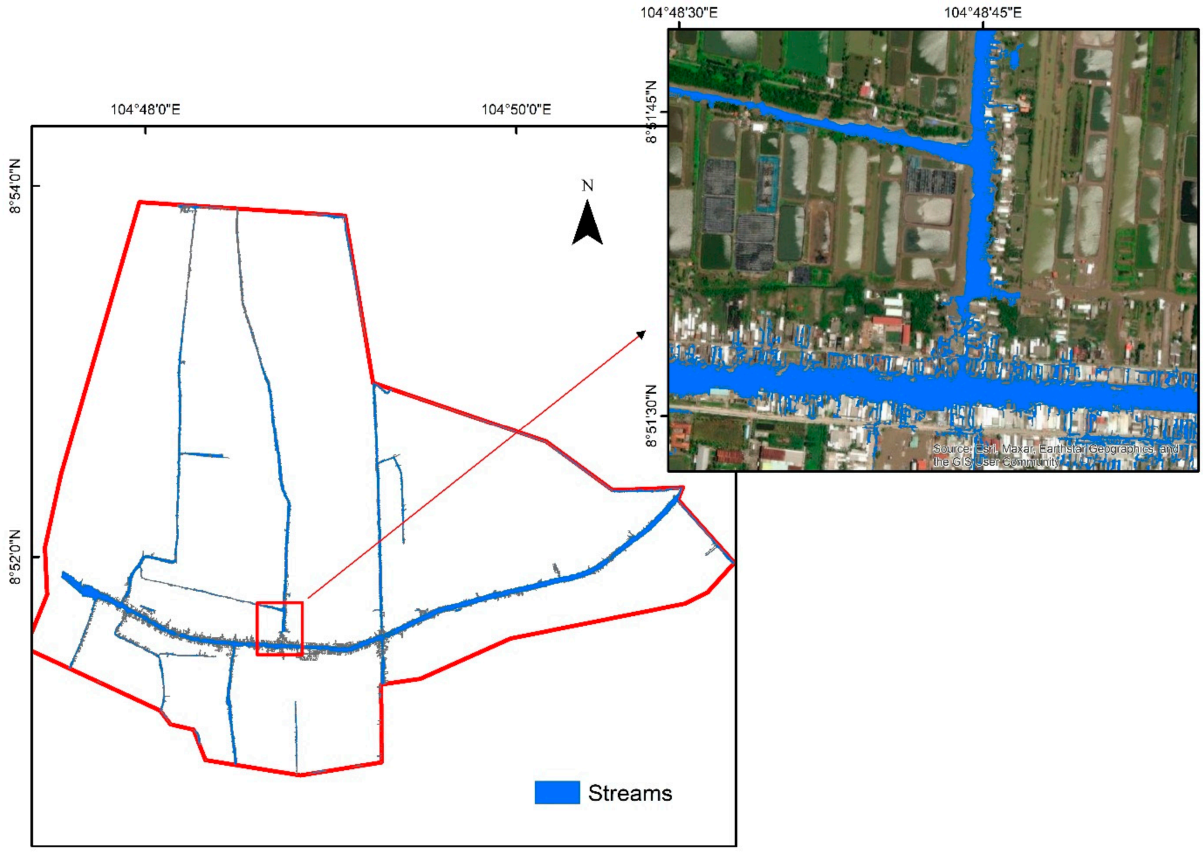

Figure 5. Stream network Map with an enlarged view over satellite imagery.

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 microchannels 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 observe two long ponds converted into eight smaller ponds) as well as the increased total number of shrimp ponds.

The Cai Doi Canal is surrounded by the majority of shrimp ponds. A more detailed view of each class's change can be seen in the final maps of shrimp ponds (Figures 6 and 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).

Table 2. LULC Change statistics from 2019 to 2022.

LULC	2022 (ha)	2019 (ha)	Change (ha)	% Change
Shrimp Ponds	148.11	174.71	−26.60	−15.20
Other Ponds	682.51	1020.01	−337.50	−33.08
Streams	67.48	109.56	−42.08	−38.40
Vegetation	1210.77	560.67	650.10	115.95
Other LULC	55.09	299.08	−243.99	−81.58

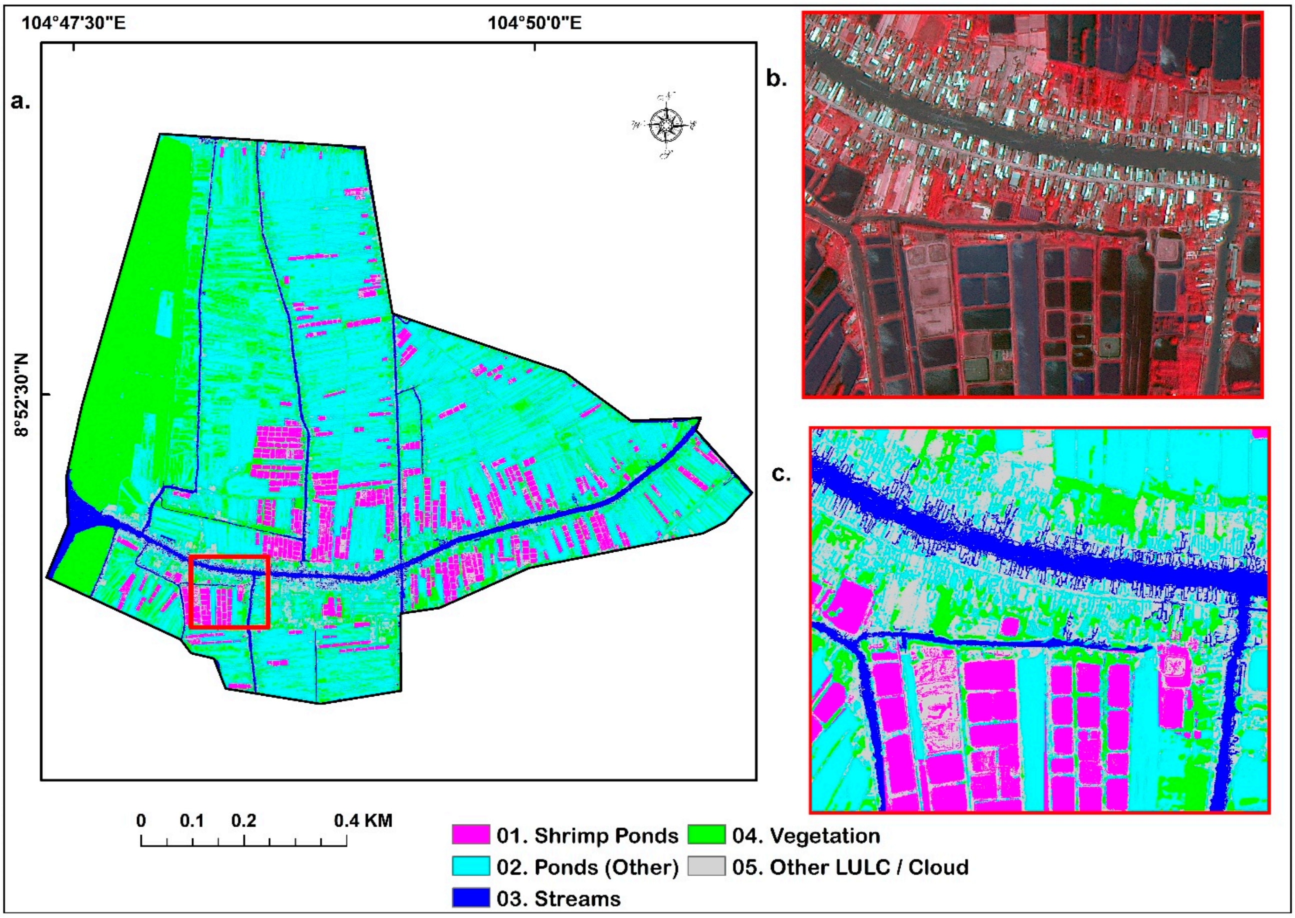

Figure 6. (**a**) Shrimp pond map of 2019 based on DMC3, (**b**) Enlarged view of classified ponds, (**c**) Enlarged view of satellite imagery.

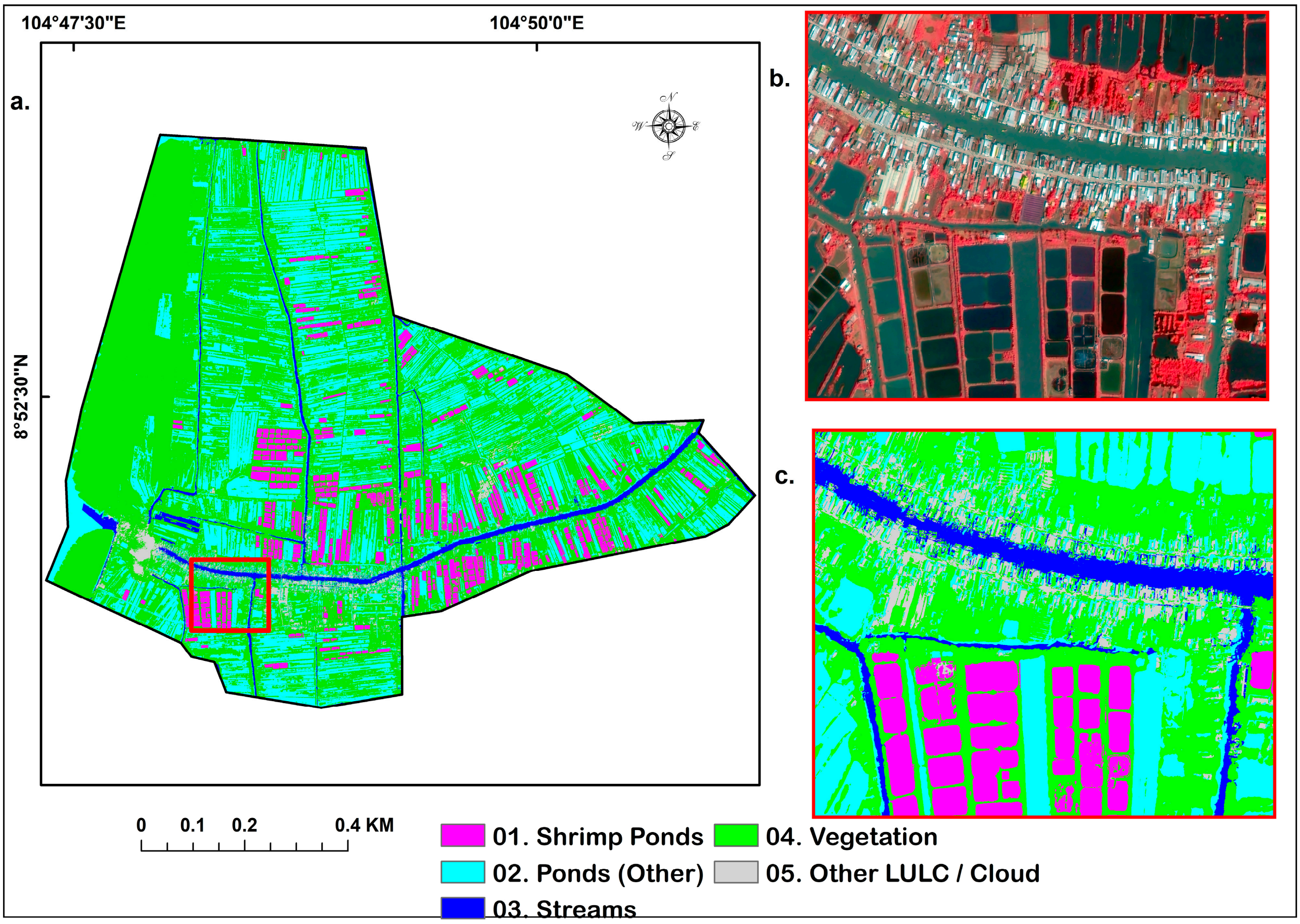

Figure 7. (**a**) Shrimp pond map of 2022 based on Jilin, (**b**) Enlarged view of classified ponds, (**c**) Enlarged view of satellite imagery.

4.4. Accuracy Assessment

The Overall accuracy of the shrimp pond classification for 2019 was nearly 87%, whereas shrimp ponds class have 90% accuracy. An error matrix was generated for Cai Doi Vam providing producers, users, and overall accuracies (Table 1).

Table 3 shows the accuracy assessment of 2022 shrimp pond classification with same 56 sample points used for the 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 and the misclassified listed as other ponds.

Table 3. Overall accuracy with producer's, user's accuracy and Kappa coefficient of 2019 & 2022.

LULC Class	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's 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%	

Table 3. *Cont.*

LULC Class	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy	Kappa Coefficient
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

Triple sat and Jilin data helped in identifying shrimp ponds with up to 90% accuracy, but in order to achieve this high accuracy, the cloud cover has to be low. Change detection was carried out for these shrimp ponds for those 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 was in the Cai Doi Vam sub-district itself (Figure 8). Further, 39 ha of other ponds in 2019 were converted into shrimp ponds in 2022.

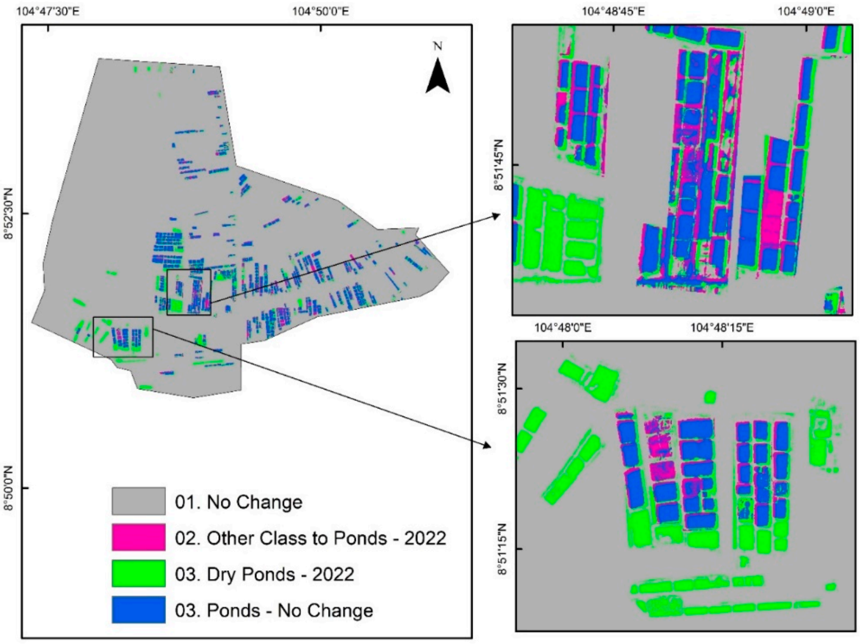

Figure 8. Change of shrimp ponds from 2019 to 2022.

Aquaculture has tremendous potential to aid in 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 is 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. Extreme weather events such as storms or flooding might have damaged ponds, leading to their reduction in size or abandonment. Natural processes like erosion, sedimentation, and coastal dynamics can also impact LULC changes, particularly in coastal regions like Cai Doi Vam [58]. Sea-level rise, storm surges, and river dynamics can alter coastal landscapes and influence the distribution of ponds and vegetation. Government initiatives to promote ecological restoration and environmental awareness prompted some farmers to restore or convert abandoned ponds back into natural vegetation to address ecological concerns [59,60].

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 [46,61,62]. It is challenging for 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 [63,64]. 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 most well known are NDWI, MNDWI, WRI, and AWEI (including AWEIsh and AWEInsh) [65]. Shrimp ponds mapped using single-date imagery for 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 the number of ponds and frequent mapping using EO data enable us to have reliable data to predict 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 policy making towards sustainable production for future years [66]. 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. Water contamination due to the use of chemicals is a major concern for shrimp farming sustainability. While the current system focuses on mapping aquaculture areas, future iterations could incorporate remote sensing techniques sensitive to water quality. Integrating multispectral or hyperspectral imagery could facilitate the detection of chemical pollution events, providing an early warning system to mitigate potential losses and protect the environment.

We also note that change detection studies with this imagery have limitations: DMC3/Triplesat has low cloud coverage; however, it also has a little lower spatial resolution compared to Jilin. Further, Jilin-1's overall accuracy was 2% higher than DMC3/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. Higher-resolution imagery offers more detailed information, enabling better discrimination of aquaculture ponds and associated features. On the other hand, lower-resolution imagery may not capture fine-scale features but can still provide an overview of the larger aquaculture landscape. Future research should explore the trade-offs between resolution and mapping accuracy to optimize the system's performance.

Integrating periodic satellite imagery updates the system and helps identify changes in aquaculture areas after a natural calamity, such as a flood event. Integrating data from other sources, such as weather data and historical records of flood events, can enhance the system's ability to understand the relationship between natural calamities and aquaculture losses. This timely information empowers local authorities and farmers to assess the extent of damage and take appropriate measures for recovery and adaptation [67].

5. Conclusions

In conclusion, the successful development of a regional-level coastal pond aquaculture map for two different time periods of 2019 and 2022 of Cai Doi Vam Township, Phu Tan District, Ca Mau Province, using high spatial resolution single-date satellite imagery and ground truth data, marks a significant step forward in sustainable aquaculture management. The system's integration of advanced satellite imagery technology and ground truth data has allowed for a comprehensive and precise mapping of aquaculture areas, providing valuable insights into the current state of coastal pond aquaculture in the region. The accuracy assessment conducted on the mapping system demonstrates its reliability in producing highly accurate results, thus enabling policymakers and stakeholders to make informed decisions based on trustworthy data. As Jilin and DMC3 satellite data are optical data vulnerable to cloud cover, this hampers the availability of data during 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 on the remarks 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. Triple sat and Jilin were not helpful in built-up and settlement classification due to the absence of the SWIR band.

Author Contributions: P.K.B.: Data curation: Formal analysis, Methodology, Writing—original draft and editing; M.K.G.: Project administration, Resources, Funding acquisition, Supervision, Writing—review and editing; P.P.: Methodology, Visualization; A.S.: Resources, Software; I.M.: Project administration, Resources, Funding acquisition, Writing—review and editing. All authors have read and agreed to the published version of the manuscript.

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