JOURNAL OF
HYDRO-METEOROLOGY

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Research Article

Integrating UAVs and AI for shrimp pond mapping: A case study in Can Giuoc district, Long An province, Vietnam

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Received: 15 August 2024; Accepted: 26 September 2024; Published: 25 December 2024

Abstract: Worldwide, the utilization of Unmanned Aerial Vehicles (UAVs) has been deployed in a wide range of resources management practices. The UAVs serve as valuable and visible tools for managing water resources, forests, agriculture, and land use change. Undoubtedly, the application of UAVs surpasses traditional methods in terms of efficiency, offering significant time and cost savings. Meanwhile, Artificial intelligence (AI) has emerged as a critical technology in the realm of information technology, particularly when it comes to image segmentation. The purpose of this study is to integrate UAVs and AI for mapping shrimp farms in Long An province, Mekong Delta. By leveraging AI, we empower systems to learn intricate image features and subsequently identify and segment objects within those images. In the context of modern agricultural management practices, we leverage UAV imagery as input data for AI systems to identify shrimp ponds, the image recognition platform is Deep Learning (DL) based on U – Net structure. Using the shrimp pond boundary on the 1:1000 scale topographic map as reference data, the results of this method showed a recall of 83.3%, corresponding to a miss rate of 16.7%. The precision of the method was 85.7%, corresponding to a misidentified shrimp pond extraction rate of 14.3%. The results suggest that the combination of UAVs and AI to mapping shrimp farms can facilitate efficient monitoring and management practices for local authorities. Thus, this integration is a promising application to assist and enable agricultural planning and regional economic development activities.

Keywords: UAV; AI; DL; Shrimp pond map.

1. Introduction

Since 1970, the global practices of shrimp farming cultivation have undergone the rapid growth of both area and intensive cultivation. Particularly, Southeast Asia is the most burgeoning region, which remains a dominance of the world's shrimp production [1]. Asian countries collectively contribute approximately 55% to the world's total shrimp exports. Notably, Vietnam stands out as one of the top three shrimp exporters globally, alongside India and Ecuador [2]. Among the top Asian shrimp exporters, India, Vietnam, Indonesia, Thailand, Bangladesh, and China contributed to nearly 92% of the regional shrimp exports [3]. As a part of the Mekong Delta's broader policy, Long An province specifically promoted the transformation of low productive rice-cultivation land into aquaculture areas. The shift of this strategic aims to enhance land utilization efficiency and boost income for the livelihoods of local households [4]. Simultaneously, this conversion initiative seeks to restructure agricultural production in specific regions and localities, leveraging the unique advantages of specific land areas and natural conditions. The ultimate goal is to foster favorable conditions for sustainable agricultural development [5–6]. Thus, Long An province has chosen shrimp cultivation as one of aquaculture's mainstay to benefit from high-tech production methods during the 2021-2025 period. To enhance production efficiency, Can Giuoc district and the broader province have actively promoted the transition from traditional shrimp practices to high-tech farming approaches. These advanced methods include multi-stage nursery ponds, bottom siphons, bottom oxygen, automatic feeding machines, frequency converters, Biofloc water treatment technology, and microbiological techniques [7].

As high-tech methods revolutionize shrimp farming, modern solutions are also employed to collect, construct, and manage aquaculture map data specifically related to shrimp. This data serves as the foundation for analyzing local climate, soil conditions, and farmers' practices and techniques in shrimp farming. Simultaneously, it plays a crucial role in land management, aligning with state policies [8].

An aircraft that operates without a human pilot onboard is commonly known as An Unmanned Aerial Vehicle (UAV). This kind of facility has evolved significantly over time and now serves a multitude of purposes, from military reconnaissance to civilian applications like aerial photography and environmental monitoring [9]. UAVs are revolutionizing global agriculture by enabling precision management of critical inputs, including the use and type of fertilizers, agrochemicals, and natural resources (soil and water). The impact of UAV applications is far-reaching such as efficiently survey implementation in large areas in a short time, offering real-time solutions through advanced data analytics tools [10]. In fact, UAVs serve as a valuable platform for efficiently managing resources and monitoring the environment, especially in the face of complex challenges posed by rapid changes in anthropogenic activities and climate change effects.

Researchers harnessed multispectral imagery captured by a UAV to monitor the cultivation of *Kappaphycus alvarezii* (commonly known as *Kappaphycus*), a type of seaweed. By estimating fresh weights of seaweed and carrageenan across different days in three cultivation cycles, they derived daily growth rates. The innovative approach of UAVs - a kind of remote sensing facility - performs an amplitude application for precision aquaculture, specifically benefiting *Kappaphycus* cultivation [11]. Due to prominent features, UAVs play a crucial role in aquaculture farm management and monitoring, particularly for offshore cages (floating fish-cage cultivation). Accordingly, UAVs assist to collect data on various parameters such as the quality and pollutants of water, temperature of water bodies, the velocity of water flow, and the behavior of fish. Equipped with sensors and advanced technologies, UAVs can even detect the cages themselves and monitor for illegal fishing activities. This integration of UAVs contributes to a precision aquaculture framework [12–14]. Previous studies have explored the use of UAVs to establish marine ecosystem zoning and create aquaculture status maps. These maps synchronize data, offer valuable information for management, and aid decision-making processes [15–16].

Recent far-reaching developments of artificial neural network, AI has brought a magnitude of its application for various areas. AI refers to the capability of machines to operate independently, without manual guidance. These AI-based systems are typically programmed for automation, and they incorporate human intelligence to make decisions, especially in critical situations [9–10]. The algorithms of image recognition constitute statistical, syntax, and pattern matching data. In recent years, advancements in neural network and support vector machine technologies have propelled image recognition to new heights [11]. Deep learning (DL), a subset of AI, operates through artificial neural networks. It excels at analyzing and processing data, simulating aspects of the human brain [12]. DL architecture encompasses both supervised and unsupervised models. In the supervised realm, different types of DL were deployed, including recurrent neural networks (RNNs), long short-term memory (LSTM), gated recurrent unit (GRU), convolutional neural networks (CNNs), and generative adversarial networks (GANs). On the unsupervised side, we encounter deep belief networks (DBNs), Deep Transfer Networks (DTNs), Tensor Deep Stack Networks (TDSN), and auto-encoders (AEs). These models play crucial roles in tasks ranging from image recognition to feature extraction [13]. The U-Net is known as a popular architecture of neural network made its debut in 2015 within the medical field. It's a DL framework specifically crafted to maximize efficiency when working with limited data while still achieving impressive speed and accuracy [14]. Accordingly, the U-Net architecture was applied for image segmentation, that features a distinctive design comprising two main components of path: the contracting path and the expansive one. In the contracting path, encoder layers extract contextual information and down sample the input's spatial resolution. In order to decode layers, the expansive path was employed to reconstruct the encoded data, leveraging skip connections that incorporate information from the contracting path. Ultimately, U-Net generates accurate segmentation maps [15]. The U-Net architecture derives its name from its distinctive "U" shape (Figure 1).

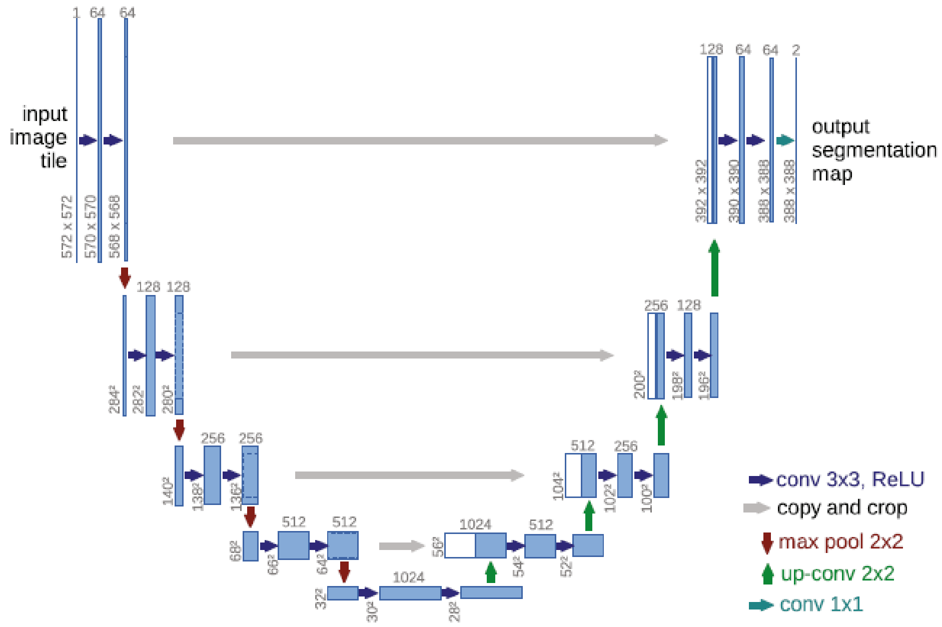


Figure 1. U-net architecture [16].

The study objective is to deploy the integration of UAV and AI for constructing shrimp pond maps with a case of Can Giuoc district, Long An province. In this study, we leverage the U-Net architecture to meticulously segment and distinguish shrimp ponds. The input data comprises processed UAV images, then transformed into detailed image maps.

2. Materials and Methods

2.1. Study area

The study area constitutes two communes (Phuoc Lai and Phuoc Vinh Tay) of Can Giuoc District, Long An province. Can Giuoc District, situated in the south-eastern part of Long An Province, which holds a significant geographical importance since it serves as a gateway to both Ho Chi Minh City and south-western provinces of the Mekong Delta area. The study area lies at approximately 10°36'15" North latitude and 106°41'44" East longitude. Its terrain resembles a river delta near the mouth, characterized by flat expansion intersected by a network of rivers and canals. Notably, 48.34% of the natural area consists of saline and alum soil, making it well-suited for high-yield aquaculture.

Situated along the banks of the Can Giuoc River, the District has emerged as a prominent hub of the provincial brackish water shrimp production. Approximately 90% of shrimp production consists of white-leg shrimp (scientifically known as *Litopenaeus vannamei*). The study area spans approximately 135 hectares and is strategically positioned within a government-invested zone dedicated to advancing shrimp farming by adopting high-tech agricultural practices.

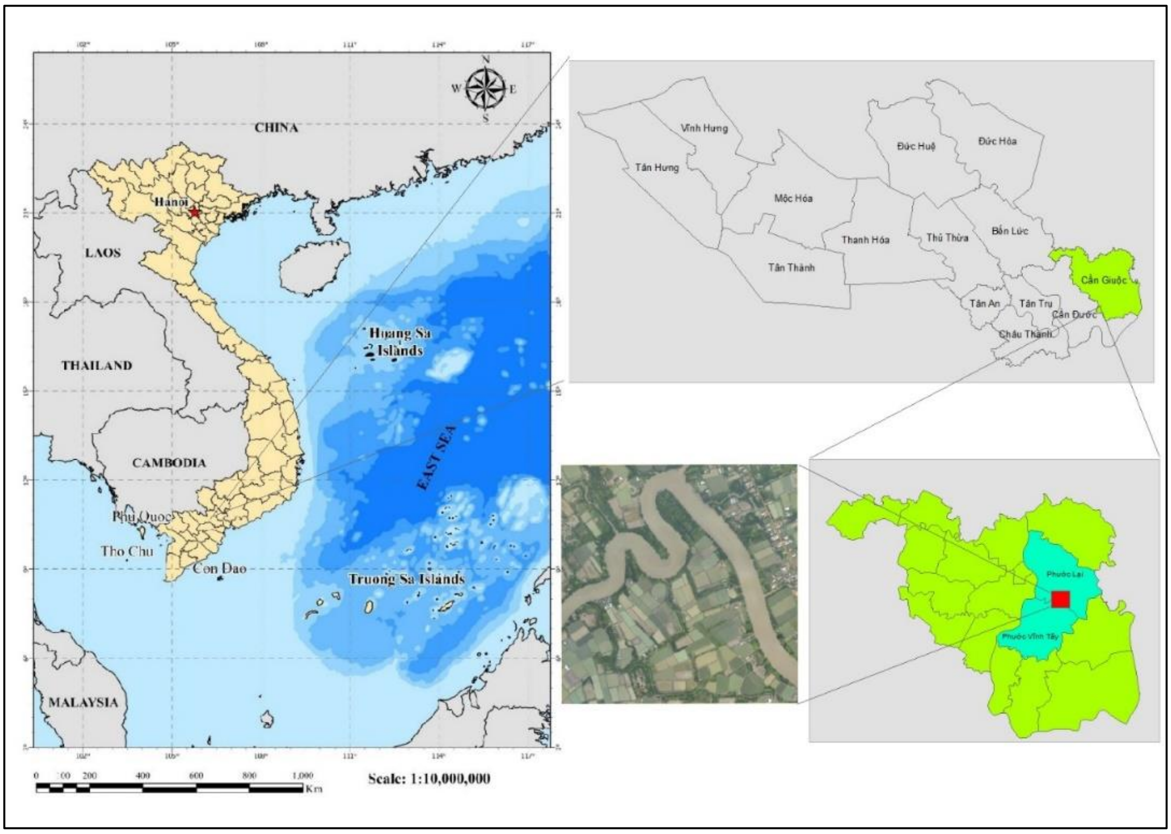
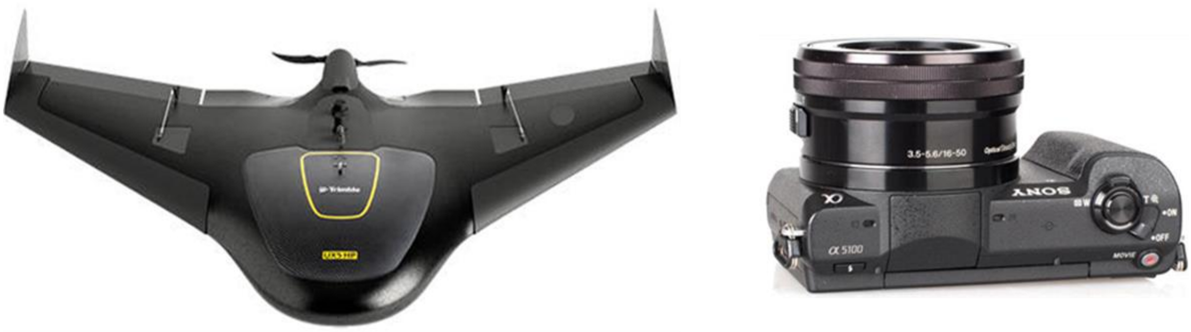


Figure 2. The study area is located between two communes (Phuoc Lai and Phuoc Vinh Tay).

2.2. Data and methods

The data collection process relies on the Trimble UX5 device, a specialized tool with a long history in mapping applications. The UX5 system comprises five key components: the aircraft fuselage, camera, ground control, launcher, and device detector. Notably, the fuselage weighs 2.5 kg, boasts a 100 cm wingspan, and features a wing area of 34 dm² enhancing UAV stability during photo capture (Figure 3a). As for imaging, the Sony A5100 camera plays a crucial role, offering a resolution of 24.3 megapixels (Figure 3b).



a) UAV UX5 b) Camera Sony A5100

Figure 3. UAV and camera attached to UAV.

The field investigation was carried out on March 30, 2023, in which flights of the UAV took place at 300 m of altitude. For coverage, both overlap tracks of along and across sides were set to 80%. Additionally, the vertical angle during the flight was 90 degrees (Figure 4).

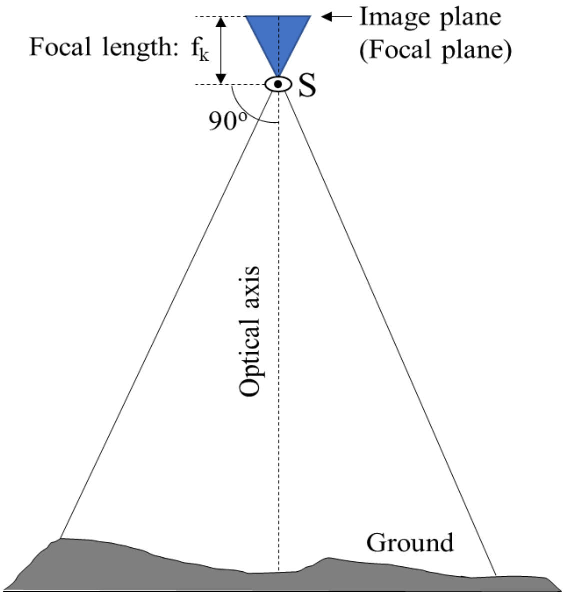


Figure 4. Camera angle is 90 degrees for all photos taken.

The Trimble UX5 utilizes advanced technology of Post Processed Kinematic - Global Navigation Satellite System (PPK GNSS) to precisely determine the location of captured images, resulting in time savings during field operations. Before feeding these images into the image processing software, their locations are adjusted and recalculated for high accuracy. Agisoft Metashape software plays a crucial role in processing the collected data. It takes the raw input and transforms it into the orthomosaic, following the steps as depicted in Figure 5.

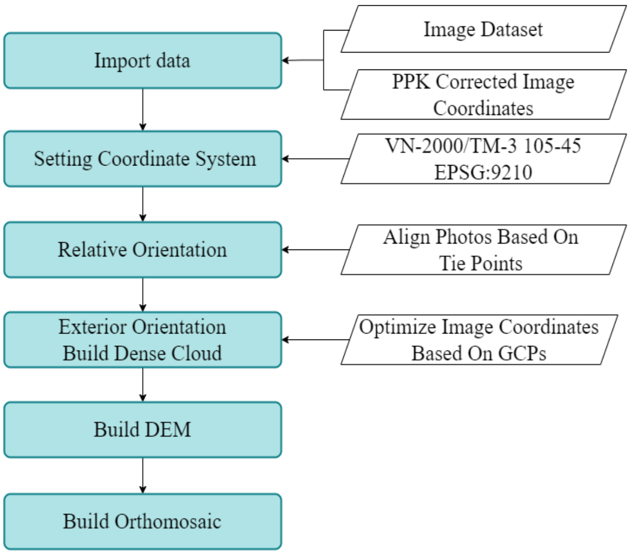


Figure 5. Procedure of image processing.

In this study, the DL model was developed and coded within the Google Colab platform, utilizing Python as the programming language. Google Colab offers access to Graphics Processing Units (GPUs), significantly enhancing model training especially when dealing with large datasets by harnessing the power of the computing cloud.

The process of using a DL model to extract shrimp ponds typically involves three phases. First, there's data preparation, where relevant imagery or data about the ponds is gathered. Next comes model training, during which the DL model learns from this collected data. Finally, model implementation is deployed to analyze new image sets and identify shrimp ponds.

During the data collection phase for shrimp pond mapping with DL, several key steps are involved. First, unprepared image data is gathered, including data captured by UAVs in the project area and other available sources. Next, preprocessing steps are performed to standardize image sizes and remove noise. The dataset is then enriched by incorporating algorithmic variables. Subsequently, the data image set is categorized into training and test data. The dataset is essential to training the DL model, while a data checker evaluates optimal values and parameters within the model (Figure 6).

In the module training phase, several key steps are involved. First, the processed dataset is assigned to the DL model using a U-Net architecture. Next, the output data is evaluated after the model is applied to the input dataset. The training dataset plays a crucial role in training the DL model. Additionally, during this step, optimization functions are tested to select the optimal parameters for enhancing the model's performance.

The model implementation phase involves several critical steps. First, the output data from the optimized DL model is digitized. Next, this digitized data is synchronized with the web application's database, where it undergoes processing and storage either on an on-premises server or in the cloud. Finally, a web application is created to facilitate end users' access to and modeling of map data. In our study, we structure the output data in two formats: raster and shapefile with polygon geometry. These formats allow us to represent spatial information effectively. Additionally, we link the results to background data available on the web. This preliminary verification process ensures the correctness of the coordinate system alignment and the accurate classification of characteristic objects.

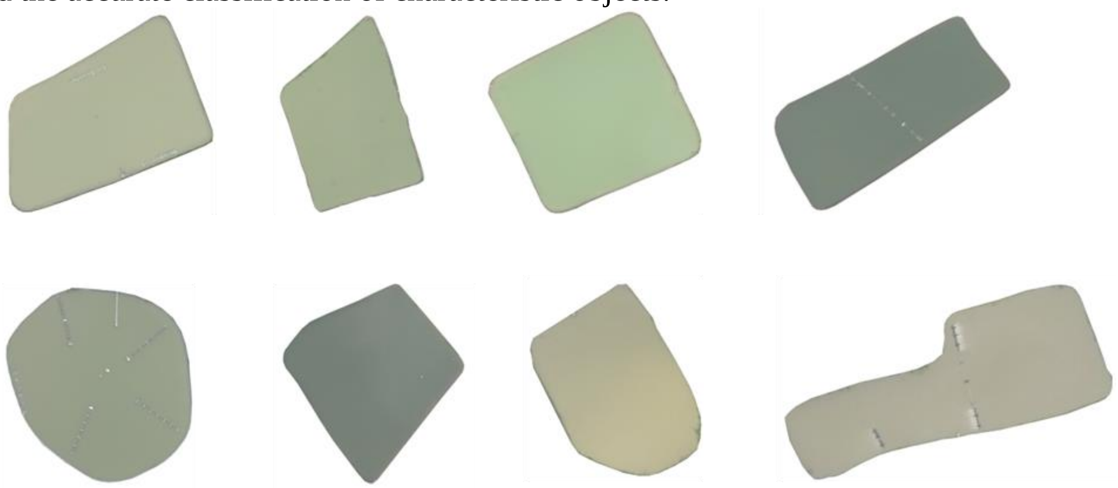


Figure 6. Different data samples of shrimp ponds.

The confusion matrix is like a trusty compass for data scientists and DL enthusiasts. It helps us navigate the performance of our models when dealing with segmentation tasks (like identifying objects within an image) or distinguishing between different classes (such as "cat" vs. "dog") (Figure 7).

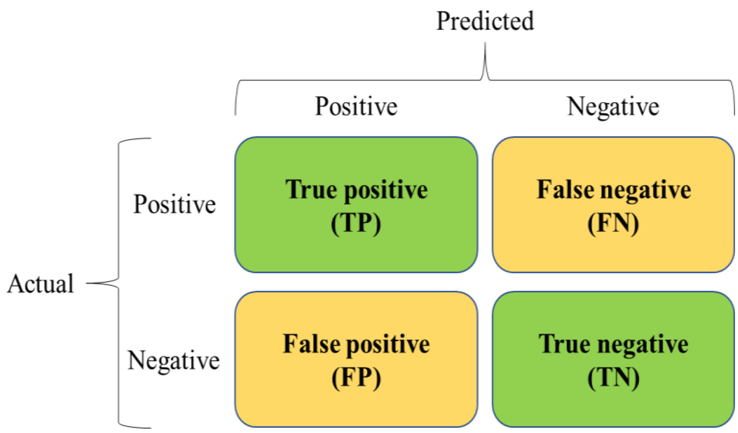


Figure 7. Confusion matrix.

The results of shrimp ponds recognition and classification from the DL model are evaluated through the parameters of precision and recall. Each evaluation parameter will have different meanings and serve different purposes. The formula for evaluating these parameters is shown as follows:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{1}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

3. Results

3.1. Identification of shrimp ponds using AI (DL)

After the DL model processes the data, the resulting output is transformed into a shapefile format (specifically, a polygon format). This shapefile is then uploaded to OpenStreetMap an excellent resource that combines features of a free and open website, an online map, a search engine, and a geodata editor. After uploading, the Shapefile data can be downloaded and further processed using ArcGIS software on a personal computer.

The verification dataset comprises a 1:2000 scale topographic map generated from UAV images. Technicians manually digitized the data layers on this map, which was officially accepted in 2023. To assess the performance of the DL model, the hydrological layer containing shrimp ponds from the topographic map was overlaid with the DL-generated shrimp pond data. A confusion matrix was then constructed by using this combined dataset to evaluate the model's accuracy (Table 1).

Table 1. The confusion matrix with data evaluation values of DL model for shrimp pond.

		Predicted based on DL	
		Shrimp Pond	Other
Topography map	Shrimp Pond	204 (TP)	41 (FN)
	Other	34 (FP)	10 (TN)

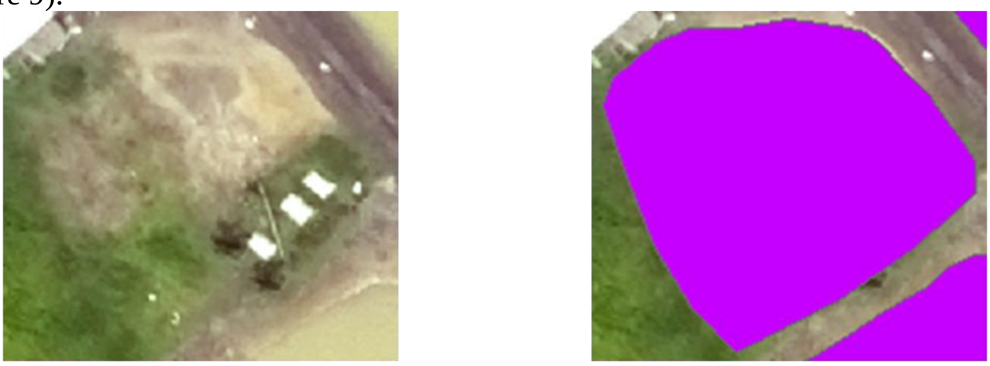
Using formulas (1) and (2) we can calculate the following results: Precision = 85.7%; Recall = 83.3%.

The detection and extraction of shrimp ponds from the DL model achieved a precision of 85.7%, showing that out of 238 shrimp ponds extracted by DL, 204 were correct, and the remaining 34 were mistakenly identified. The reason for the mistake was the similarity in shape and color between shrimp ponds and rice fields that had not been sown or had newly grown rice plants that were still very small (Figure 8).

a) Shrimp pond b) Rice paddy field

Figure 8. Similarity in shape and color between shrimp pond and rice paddy field.

The recall of the DL model when identifying shrimp ponds is 83.3%, showing that out of 245 shrimp ponds on the topographic map, DL correctly identified 204 shrimp ponds, while the remaining 41 shrimp ponds were missed and could not be identified by the DL model. This shortcoming comes from the fact that the actual shrimp ponds at the time of taking the photos were abandoned, leading to water drying up and weeds covering the ponds (Figure 9).



a) Abandoned shrimp pond on UAV images b) Shrimp pond in totographic map

Figure 9. Similarity in shape and color between shrimp pond and rice field.

3.2. Shrimp pond map editor

In the study area, the shrimp ponds exhibit consistent shapes. Their total area amounts to 42.4 hectares, which corresponds to 31.4% of the entire area (135 hectares). On average, each shrimp pond covers 1843.8 m^2. Interestingly, there's one pond specifically designed in a circular shape for shrimp larval cultivation.

In the center of this area lies the Rach Van River, dividing it between the two communes (Phuoc Lai and Phuoc Vinh Tay). The meticulously edited map of shrimp ponds is rendered at a scale of 1:5000 (Figure 10). Amidst this landscape, scattered rice fields dot the terrain some still under cultivation, while others lie abandoned due to the challenges of low rice productivity.

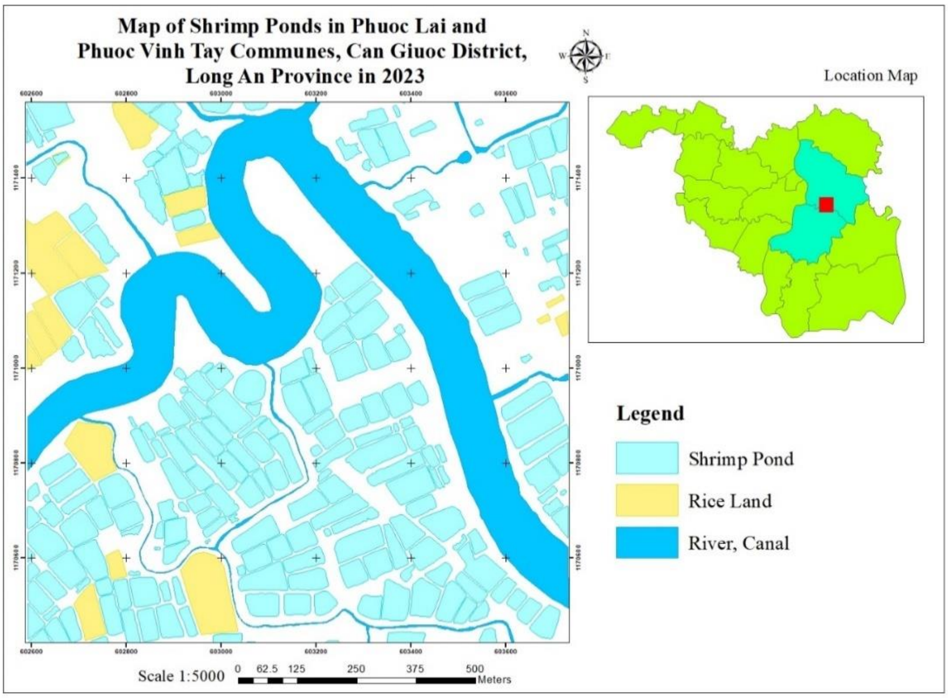


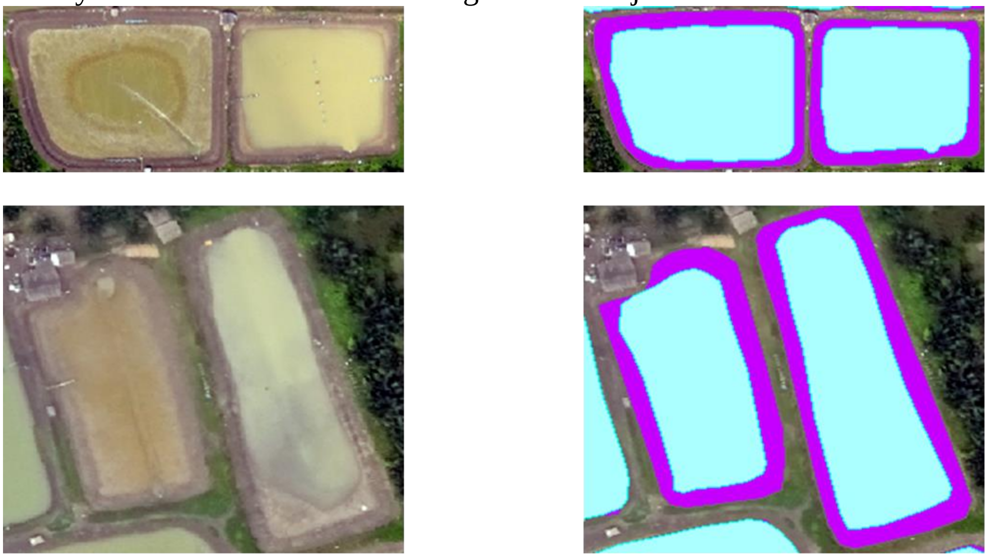
Figure 10. Map of Shrimp Ponds in two communes (Phuoc Lai and Phuoc Vinh Tay) in 2023.

4. Discussion

In our study, we employed DL technology based on the U-Net architecture to extract shrimp ponds. The achieved accuracy of 85.7% and recall of 83.3% is commendable, although it falls short when compared to previous studies focused on object extraction. Notably, Farajzadeh and colleagues successfully extracted building footprints with an impressive accuracy of 97% and a recall of 91% [25]. The key lies in the distinct features of buildings clear shapes and colors which facilitate their recognition. Additionally, Farajzadeh et al. leveraged a combination of orthomosaics and Digital Surface Models (DSMs), where buildings of varying heights were represented in different colors. This approach led to highly accurate and well-recalled building footprint extraction, minimizing misclassification and omission.

During our study, we encountered an important consideration when extracting shrimp pond boundaries: situations where the waterline and the actual shrimp pond boundary do not align perfectly. Dry ponds, in particular, exhibit this discrepancy, which can lead the DL model to mistakenly identify the waterline as the pond boundary (Figure 11). To address this, specific parameters must be fine-tuned for the DL model when identifying shrimp ponds in such cases.

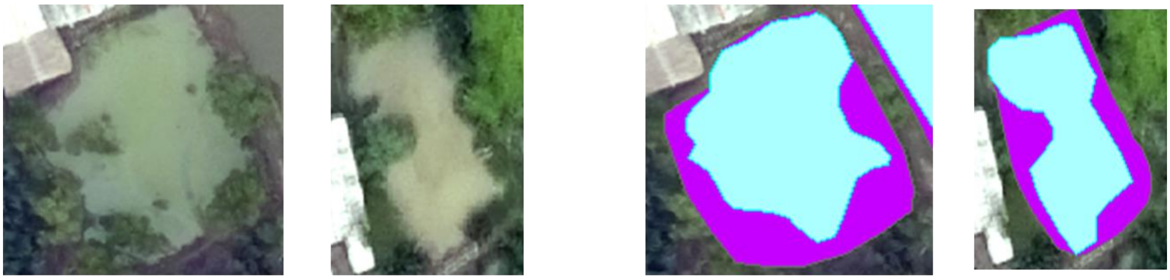
Another challenge arises when extracting shrimp ponds using DL: the robust growth of trees within these ponds. Sometimes, trees can obscure parts of the pond boundaries, complicating the extraction process (Figure 12). To address this issue, field investigations and surveys become essential for making accurate adjustments.



a) Shrimp Ponds in UAV images

b) Shrimp Ponds (Blue green pastel polygon is the pond created by DL, the dark violet polygon is the pond on the topographic map

Figure 11. The waterline and the shrimp pond boundary do not coincide.



a) Shrimp Ponds in UAV images

b) Shrimp Ponds (Blue green pastel polygon is the pond created by DL, the dark violet polygon is the pond on the topographic map

Figure 12. Shrimp pond boundary covered by vegetation.

5. Conclusion

AI is gradually becoming familiar in various fields. When we use DL technology with image recognition, it significantly reduces the need for manual digitization, ultimately saving valuable time and effort.

In our research, achieving an accuracy of 85.7% and a recall of 83.3% for shrimp ponds extraction is a positive outcome. It underscores the successful synergy between remote sensing technology particularly utilizing UAV images and AI techniques. Notably, this approach isn't limited to shrimp ponds alone; it holds promise for creating other thematic maps as well.

However, there is no coincidence of waterline and shrimp pond boundary or shrimp pond boundary covered by vegetation. These are the problems that this study encountered, making it difficult for the DL model to accurately segment the image. Future studies on this hurdle should be made to improve precision.

To enhance work efficiency, we recommend combining the U-Net architecture with other neural network architectures within the DL model. Additionally, if feasible, leveraging multispectral data collected from UAVs as input material for the DL image recognition model holds great promise. This approach can lead to more accurate and comprehensive results in identifying and mapping features like shrimp ponds.

Authors' contribution: Conceptualization: T.N.H.T., V.L.P.; Methodology: L.V.T., T.N.H.T.; Data collectiong and processing: T.N.H.T.; Writing - original draft: T.N.H.T., V.L.P., L.V.T.; Writing, reviewing and editing: T.N.H.T., V.L.P.

Declaration: The authors declare that there is no conflict of interest among them. This article is the findings of their own studies, not previously published elsewhere, and not copied from previous studies.

Acknowledgements: We would like to express our thankfulness to Ho Chi Minh City **University** of Technology (HCMUT), VNU-HCM for the support of time and facilities for this study.

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