Aquaculture Pond Precise Detection and Monitoring for Spacial Planning Using Deep Learning and Remote Sensing

Susank Chigilipalli , Maritime Research Center Intern

Introduction

Coastal aquaculture, particularly the cultivation of shrimp, has experienced significant growth due to the high demand for seafood. However, this rapid expansion poses numerous environmental challenges, such as the destruction of mangroves and natural habitats, pollution, and increased carbon emissions. This note focuses on the identification and monitoring of aquaculture ponds using advanced remote sensing and deep learning techniques. The aim is to identify aquaculture ponds, provide accurate geographic coordinates, and track spatiotemporal changes to support sustainable aquaculture practices and marine spatial planning.[1][2]

The method developed in this study is capable of rapidly and accurately mapping coastal aquaculture ponds, which is significant for marine resource management and promoting sustainable development. Historically, the statistical survey method based on entity detection was the most common information extraction strategy, though it was limited by technology. While surveys were accurate and technologically friendly, they were also time-consuming and labor-intensive (Hardin and Jensen 2011; Safi Khani et al. 2022). Currently, the entity survey method is often used for accuracy verification based on ground truth. Remote sensing has emerged as an efficient method of earth observation (Guo et al. 2020; Bratic, Yordanov, and Brovelli 2023). Compared with traditional methods, remote sensing technology offers a larger observation scale (Chen et al. 2022a; Zhao et al. 2023a and 2023b), more convenient access (Wang et al. 2021), richer data expression (Peterson, Sagan, and Sloan 2020), and a more complete observation perspective, meeting the requirements for rapid and accurate extraction of aquaculture pond information (Cheng et al. 2020; Peng et al. 2022a; Mahmood, Zhang, and Li 2023).

Study Area and Data Sources

The study focuses on the coastlines of Andhra Pradesh, West Bengal, and Gujarat in India. These regions are significant for aquaculture due to their extensive coastlines and favorable conditions for shrimp farming. The primary data sources used in this study include Sentinel-2 satellite imagery and OpenStreetMap data. Sentinel-2 images provide high-resolution multispectral data, essential for detailed analysis and mapping of aquaculture ponds.

Identification of Filled Ponds:

DeepLabv3 with NDWI Initial Segmentation and Random Forest Final Classification

Methodology

Image Processing and Data-set Preparation

The methodology involves multiple steps to ensure accurate identification and monitoring of aquaculture ponds. The process begins with the preprocessing of Sentinel-2 imagery, including atmospheric correction and cloud masking to remove noise and enhance image quality.

Normalized Difference Water Index(NDWI):

The Normalized Difference Water Index (NDWI) is a well-regarded technique for identifying water bodies in satellite imagery by leveraging the distinct reflectance properties of water compared to other land cover types. NDWI utilizes the green (G) and near-infrared (NIR) spectral bands in its calculation:

$$NDWI = \frac{Green - NIR}{Green + NIR}$$

This index is particularly effective in highlighting water features because water bodies strongly absorb NIR light while reflecting green light, resulting in higher NDWI values for water compared to other surfaces.

The Normalized Difference Water Index (NDWI) is highly sensitive to the presence of water, making it efficient in delineating water bodies even in heterogeneous landscapes. This sensitivity helps in distinguishing water from built-up areas, soil, and vegetation, which may not be as effectively separated using other indices like the Normalized Difference Vegetation Index (NDVI). NDWI's effectiveness lies in its ability to provide a clear demarcation between water and other land cover types. Compared to NDVI, which relies on the red and NIR bands and often misclassifies densely vegetated areas as water due to high NIR reflectance, NDWI provides a more accurate identification of water bodies.

NDWI's robustness is also demonstrated through its successful application across various environments, from urban areas to natural landscapes, indicating its versatility in different geographic contexts. Unlike NDVI, which can sometimes be confused by vegetation, NDWI reduces this noise by leveraging the green band, offering a clearer distinction between vegetation and water. Additionally, the index's ability to effectively separate water from other surfaces enhances its applicability for diverse environmental monitoring tasks, making it a valuable tool in remote sensing for water body identification [3][4].

Extraction of Aquaculture Ponds Based on the DeepLabv3 Deep Learning Model:

The identification of aquaculture ponds is performed using a DeepLabv3 deep learning model, initially segmented by NDWI and finalized with Random Forest classification. This approach leverages the strengths of deep learning for feature extraction and traditional machine learning for classification accuracy.

DeepLabv3 is used in this study for aquaculture pond mapping over other deep learning architectures for several reasons related to its advanced features and proven performance in semantic segmentation tasks. Here are the key reasons:

DeepLabv3 employs aurous (dilated) convolutions, which enable the model to capture multi-scale contextual information without sacrificing spatial resolution. This capability is crucial for identifying and delineating the boundaries of aquaculture ponds, which can vary significantly in size and shape. The architecture integrates an aurous spatial pyramid pooling (ASPP) module, which examines an input image at multiple scales by applying aurous convolution with varying rates. This mechanism enhances the model’s ability to recognize objects at different scales, improving its robustness and accuracy in segmenting features with varying dimensions, such as ponds within a landscape.

DeepLabv3 has demonstrated superior performance in benchmark datasets for semantic segmentation, including PASCAL VOC and Cityscapes. Its design optimizes both boundary delineation and the recognition of small and large objects, making it exceptionally well-suited for tasks that require precise segmentation, such as identifying aquaculture ponds from satellite imagery. Compared to other architectures like U-Net, FCN, or SegNet, DeepLabv3 often achieves better performance in terms of mean Intersection over Union (mIoU), a common metric for evaluating segmentation quality. Its superior performance is attributed to its sophisticated design, which effectively balances local and global feature extraction.

The DeepLabv3 architecture is flexible and can be combined with different backbone networks (e.g., ResNet, Xception; in our case, ResNet) to balance between accuracy and computational efficiency. This adaptability allows for tailoring the model to the specific requirements of the study, such as the need for higher accuracy or faster processing times. Additionally, aquaculture ponds can exhibit diverse visual characteristics due to varying water quality, vegetation, and surrounding land use. DeepLabv3's ability to integrate multi-scale context and handle fine details ensures robust segmentation of ponds across different scenarios, enhancing the reliability of the mapping process.[5]

Training

Training involves using images of ponds or clusters of ponds to train the neural network. This process includes image segmentation followed by Random Forest training with shape parameters to classify the parameters identified from the segmented images accurately.

Identification

The identification process follows this structured pipeline [6]:

- **NDWI images**: Preprocess the NDWI mosaics for initial water body detection.
- **DeepLabv3 Segmentation**: Use the DeepLabv3 model to segment the image.
- **Shape Parameter Extraction**: Extract shape parameters from the segmented image.
- **Final Classification**: Apply Random Forest classification for the final identification of aquaculture ponds.
- Finding boundary, calculating the area, finding out the centroid, and coordinates of the pond.

Advantages of the Combined DeepLabv3 and Random Forest Approach

The integration of DeepLabv3 for segmentation and Random Forest for classification offers a powerful and precise solution for aquaculture pond identification. By leveraging the strengths of both deep learning and traditional machine learning, this approach ensures high accuracy in recognizing complex shapes and varying pond sizes. This dual-method strategy excels in capturing intricate details, providing a robust and reliable means of pond identification and classification.

One of the key advantages is the high level of accuracy achieved through this combination. DeepLabv3's advanced segmentation capabilities, paired with the Random Forest's proficient classification, result in exceptional accuracy for complex and diverse aquaculture pond shapes. This accuracy is further enhanced by incorporating shape parameters such as area, perimeter, centroid, hull, and circularity. These parameters allow for detailed polygonal boundary definitions and comprehensive shape analysis, facilitating more refined and nuanced interpretations of the ponds.

The robustness of this method is highlighted by the use of the Normalized Difference Water Index (NDWI) for initial water body identification. NDWI effectively isolates relevant areas, ensuring that the subsequent segmentation process is concentrated on actual water bodies. This initial step is crucial for directing the segmentation towards pertinent regions, enhancing the overall efficiency and effectiveness of the approach.

Versatility is another significant benefit of this method. It accommodates a wide range of aquaculture pond shapes and sizes, demonstrating its adaptability to various conditions. Moreover, the method can integrate additional features, such as water quality parameters, to further refine the classification process. This adaptability extends to handling multiple histogram peaks, making the method resilient under different image conditions and ensuring consistent performance across diverse scenarios.

The comprehensive nature of the pipeline is also a noteworthy advantage. By combining NDWI for initial segmentation, DeepLabv3 for detailed shape analysis, and Random Forest for final classification, this approach ensures a thorough and holistic processing of data. This comprehensive pipeline not only enhances the accuracy and reliability of the results but also provides a complete framework for aquaculture pond analysis, from initial identification to detailed classification.

Calculation of Cumulative Unfilled Aquaculture Ponds area:

A direct method can be involved to get the cumulative area of unfilled ponds(This method of calculating cumulative filled ponds area can be used in tracking spatiotemporal changes of a large area) by subtracting the area of ponds demarcated by the NDWI from the area demarcated by a specific band combination (such as the 11, 4, and 12 bands of Sentinel-2). This approach can help in distinguishing unfilled aquaculture ponds from filled ones by leveraging the differences in spectral characteristics between water and other features. Here are the steps involved:

- **Preprocessing**
  - **Atmospheric Correction**: Correct the Sentinel-2 imagery for atmospheric effects.
  - **Cloud Masking**: Remove clouds and their shadows using the QA60 band.

- **NDWI Calculation**
  - Calculate the NDWI using the green (Band 3) and near-infrared (NIR, Band 8) bands:
$$NDWI = \frac{Green - NIR}{Green + NIR}$$
  - Threshold the NDWI image to demarcate water bodies.
- **Band Combination Analysis**
  - Create a false-color composite using the SWIR (Band 11), Red (Band 4), and another SWIR (Band 12) bands. This combination is effective for identifying water content and vegetation.
- **Difference Calculation**
  - **Identify Water Using NDWI**: The thresholder NDWI image will highlight areas with water.
  - **Identify Areas Using Band Combination**: The 11, 4, and 12 band combination images will highlight areas with different spectral signatures, including soil, vegetation, and possibly dry or unfilled ponds.

- **Random Forest Classification on post-processed and segmented images of NDWI and (11, 4, and 12) bands**
  - To classify whether it is an aquaculture pond or natural water body, and give all such ponds for area calculation.

Advantages

- **Direct Comparison**: This method directly compares spectral signatures, making it straightforward to implement and interpret.
- **Highlighting Discrepancies**: The subtraction process highlights areas where spectral properties differ, aiding in the identification of unfilled ponds.

General Pipeline for Classifying Ponds as filled or unfilled Using NDWI Index:

- **Data Collection and Initial Demarcation**
  - Collect Sentinel-2 data focusing on Red (Band 4), NIR (Band 8), and SWIR (Band 11) bands.
  - Perform initial demarcation and identification of potential water bodies using these bands.
- **NDWI Calculation**
  - Compute the Normalized Difference Water Index (NDWI) for each pixel using the Green (Band 3) and NIR (Band 8) bands to highlight water bodies.
- **Image Segmentation with DeepLabv3**
  - Train a DeepLabv3 model on labeled datasets to segment water bodies.
  - Apply the trained model to the initially demarcated images for accurate segmentation and identification of water bodies.
- **Post-processing and Shape Feature Extraction**
  - Refine the segmented images using morphological operations.
  - Extract shape features such as area, perimeter, and centroid to analyze the characteristics of the identified ponds.
- **Random Forest Classification**
  - Use the extracted shape features to train a Random Forest classifier.
  - Classify the segmented water bodies to determine whether they are aquaculture ponds or natural ponds.
- **Centroid Coordinates Extraction**
  - Identify the latitude and longitude of the centroid of each classified pond.
- **NDWI-Based Confirmation**
  - Go to the coordinates of the centroid in the NDWI image.
  - Analyze the NDWI value at this specific point to confirm whether it is an aquaculture pond based on the NDWI threshold.

Advantages

- **Precision in Classification**: Ensures a precise classification of pond status using NDWI values at the centroid.

- **High Accuracy in Segmentation**: DeepLabv3 provides accurate segmentation, accommodating complex pond shapes.
- **Automated Process**: Reduces manual intervention and enables large-scale monitoring.
- **Robust against Noise**: Effective in distinguishing water bodies from other land cover types.

Tracking Spatiotemporal Changes in Ponds

A decision-tree classifier to identify the pond is used to quantify the spatiotemporal distribution of aquaculture ponds over the last 30 years. This involves setting specific time windows, sorting images by cloud cover, and visual inspection to ensure image quality. The analysis reveals trends and drivers of coastal aquaculture pond dynamics, providing insights into the effects of urbanization, pollution, and climate change.

Over the past 30 years, tracking the spatiotemporal distribution of aquaculture ponds has revealed significant changes. Coastal aquaculture ponds, which provide high-quality fish protein for billions of people, are increasingly threatened by urbanization, pollution, and climate change. Additionally, the expansion of large aquaculture ponds has led to negative impacts, such as the shrinkage of natural wetlands and mangroves and the deterioration of water quality. Understanding the trends and drivers behind these changes on a national and local scale remains a challenge.

Comprehensive thematic maps of aquaculture ponds are essential for effective management and environmental protection. In 2016, the FAO recommended the use of remote sensing and GIS technology to investigate aquaculture distributions. The methods for efficiently mapping aquaculture ponds have evolved from visual interpretation (Pattanaik and Narendra Prasad, 2011) to object-oriented classification (Ottinger et al., 2017, Zeng et al., 2019) and deep learning (Cheng et al., 2020). However, coarse study period intervals can lead to the loss of important dynamic information, especially in recent years.

To address this in the Chinese coastal frontier (Yuanqiang Duan, Bo Tian, Xing Li b, Dongyan Liu, Dhritiraj Sengupta, Yujue Wang, Ya Peng et al., 2021) applied a model to track changes in aquaculture ponds, using five-year intervals from 1990 to 2005 and three-year intervals from 2005 to 2020. The process involves three key steps:

1. Setting the time window from April to October each year, which corresponds to the period of vegetation growth and pond culturing, to filter images with a high contrast between the target and background.
2. Sorting the image collection based on the “CLOUD_COVER” attribute and prioritizing images with the least amount of cloud cover.
3. Judging the quality of the auto-filtered images via the visualization interface of the GEE platform to ensure they are cloud-free and clear.

Here the holding area change rate (HACR), cumulative area changes rate (CACR), and transfer-out rate (TOR) to reveal the dynamics of China’s coastal aquaculture ponds are calculated to track spatiotemporal changes.

Estimating Longevity and Age of Aquaculture Ponds:

Aslan established a set of simple rules for estimating the longevity of aquaculture ponds (Aslan et al. 2016; Aslan et al. 2021). These rules are based on the longest observation period, but the calculation results are easily affected by missing values in the observations. Specifically, the estimation results fluctuate when there are no observations in a certain year or when the observations are incorrect. Remote sensing images, influenced by the production cycle and weather, may not always show aquaculture ponds in use. After the harvest period, the traits of aquaculture ponds differ from those during the production period. Therefore, in our estimation, we began with the year of the first occurrence of aquaculture ponds and ended with the year of the last occurrence. If there were two or more consecutive years with no aquaculture ponds observed, the sequence was divided into two observation periods. The first period began with the initial occurrence of aquaculture ponds and ended with the first non-aquaculture observation. The second period began with the second occurrence of aquaculture ponds and ended with the last consecutive aquaculture pond observation.

Comparative Analysis for Estimating Longevity and Age of Aquaculture Ponds

- **Feature Extraction**
    - Extract temporal features from the time series data of each pond, such as changes in area, shape, and spectral signatures.
    - Compute additional features like the duration of filling and drying cycles and variations in vegetation around the ponds.
- **Temporal Convolutional Networks (TCNs)**

a. Model Selection:

- We choose a TCN architecture for its ability to handle sequence data and capture long-range dependencies. TCNs are well-suited for time-series prediction tasks due to their use of dilated convolutions.

b. Model Training:

- Train the TCN model on the time series data to predict future states of the ponds.
- Use historical data to train the model to recognize patterns that indicate the aging and potential lifespan of the ponds.

Advantages and Disadvantages

Advantages:

- **High Accuracy:** TCNs capture long-term dependencies in time series data, leading to accurate predictions.
- **Scalability:** The approach can be applied to large datasets from different regions and time periods.
- **Insightful Analysis:** Temporal analysis provides insights into the lifecycle and sustainability of aquaculture ponds.

Temporal Convolutional Networks (TCNs) vs. Long Short-Term Memory Networks (LSTMs) for Time Series Analysis

Temporal Convolutional Networks (TCNs) and **Long Short-Term Memory Networks (LSTMs)** are both powerful architectures for time series analysis, but they have distinct characteristics that can make one more suitable than the other depending on the specific application.

TCN Architecture

TCNs use causal convolutions to ensure that predictions are made using only current and past data, maintaining the temporal order of the sequence. They incorporate dilations to exponentially increase the receptive field without a proportional increase in the number of parameters. This allows TCNs to capture long-range dependencies efficiently.

Strengths of TCNs:

- **Parallelism and Training Efficiency**: Unlike LSTMs, TCNs allow parallel processing of input sequences, leading to faster training times, which is beneficial when working with large datasets like those from Sentinel-2.
- **Long-range Dependencies**: Due to dilated convolutions, TCNs can capture long-range temporal dependencies more effectively than LSTMs, which may struggle with very long sequences, making them suitable for analyzing multi-year satellite imagery data.
- **Stable Gradients**: TCNs are less prone to the vanishing gradient problem, often encountered in RNN-based architectures like LSTMs, providing more stable and reliable learning for long-term dependencies.
- **Flexibility**: TCNs can be easily adjusted to handle varying input sequence lengths due to their convolutional nature.

References:

1. Ahmed, N., & Thompson, S. (2019). The blue dimensions of aquaculture: A global synthesis. Aquaculture and Fisheries, 4(3), 149-155.
2. Jayanthi, M., Ramachandran, P., & Thirumurthy, S. (2021). Dynamics of land-use changes and their future trends using spatial analysis and the CA-Markov model—A case study with a special emphasis on aquaculture development in India. Environmental Monitoring and Assessment, 193(2), 67.
3. McFeeters, S. K. (1996). The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. *International Journal of Remote Sensing*, 17(7), 1425-1432.
4. Halder, T., Chakraborty, D., Pal, R., Sarkar, S., Mukhopadhyay, S., Roy, N., & Karforma, S. (2019). A hybrid approach for water body identification from satellite images using NDWI mapping and histogram of gradients.
5. Chen, L.-C., Papandreou, G., Kokkinos, I., Murphy, K., & Yuille, A. L. (2017). Deep lab: Semantic image segmentation with deep convolutional nets, aurous convolution, and fully connected CRFs. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 40(4), 834-848.
6. Hou, Y., Zhao, G., Chen, X., & Yu, X. (2022). Improving Satellite Retrieval of Coastal Aquaculture Pond by Adding Water Quality Parameters. *Remote Sensing*, 14(14), 3306.