IDENTIFYING ACTIVITY STATUS OF AMAZONIAN FISHPONDS USING REMOTE SENSING

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ABSTRACT

Aquaculture in the Amazon has emerged as a solution for food security and income generation, addressing declining natural fish stocks. This study assesses the use of remote sensing to identify and monitor aquaculture ponds, determining whether they are active (stocked with fish) or inactive. We used in situ remote sensing reflectance (Rrs) and water quality data including chlorophyll-*a* concentration, turbidity and Normalized Difference Chlorophyll Index, to identify active ponds. Data were collected at Embrapa's experimental ponds in Palmas-TO across an entire production cycle (Aug/23 to Feb/24) on different aquaculture systems. Rrs was simulated for PlanetScope's SuperDove orbital sensor (Rrs-Dove) and classified using: Spectral Angle Mapper, Euclidian distance and Mahalanobis distance. Mahalanobis distance achieved the best performance with an overall accuracy of 83%. Notably, Rrs-Dove successfully identified 100% of inactive ponds and 75% of active ponds. This approach offers a valuable tool for sustainable and strategic aquaculture management in the region.

Key words — Water Colour Remote Sensing, Aquaculture, Bioeconomy, Fishponds, Sustainability.

1. INTRODUCTION

Aquaculture plays a vital role in food security and income generation for local communities but faces challenges such as environmental degradation, unregulated growth, and the need for efficient water resource management [1]. In the Legal Amazon region, fish production has grown significantly and has emerged as an effective food security and income generation solution, addressing declining natural fish stocks [2]. In the context of inland aquaculture, many remote sensing studies have focused on mapping fishponds and distinguishing them from other natural or artificial water bodies [3–6], but there is a knowledge gap regarding their actual production status, in particular whether these ponds are actively being used.

By "active pond", we mean one that contains fish stocks and is actively managed for harvest. Some ponds may contain fish but are not being monitored for production. Therefore, "active" or "with fish stock" refers specifically to ponds receiving treatments aimed at producing fish for commercialization.

Remote sensing provides a comprehensive view of fishponds, overcoming the limitations of in situ observations and allowing large-scale analysis across temporal and spatial boundaries [1,7]. Continuous monitoring of fishpond conditions through remote sensing can help optimize production [5] while minimizing negative environmental impacts, such as eutrophication and contamination of adjacent waters. Despite the advantages, there is still a gap in the application of water colour remote sensing to inland aquaculture due to the predominance of small fishponds in the Amazon region. About 95.8% have less than 5 hectares of water surface [8].

CubeSats, a class of small satellites, offer promising opportunities for monitoring inland fishponds, especially those with smaller dimensions. PlanetScope, a CubeSat constellation, provides daily images with high spatial resolution (3.7 m) and multispectral bands, making it an excellent tool for studying the dynamic nature of fishpond systems. PlanetScope with its fine spatial and temporal resolution (1 day) is especially suited to capture changes in these smaller and dynamic environments [9].

The core hypothesis of this study is that water colour remote sensing can differentiate active farming fishponds stocked with native Amazonian species at commercial densities from empty ponds or without stock density.

2. MATERIAL AND METHODS

The data acquisition was conducted at the Experimental Center of Embrapa Fisheries and Aquaculture (CEAQ), located in Palmas, Tocantins (TO), North Brazil (Figure 1). In situ measurements were collected throughout the entire production cycle, which spanned 7 months, from August 2023 to February 2024. In total we analyzed 83 in situ samples from the fishponds.

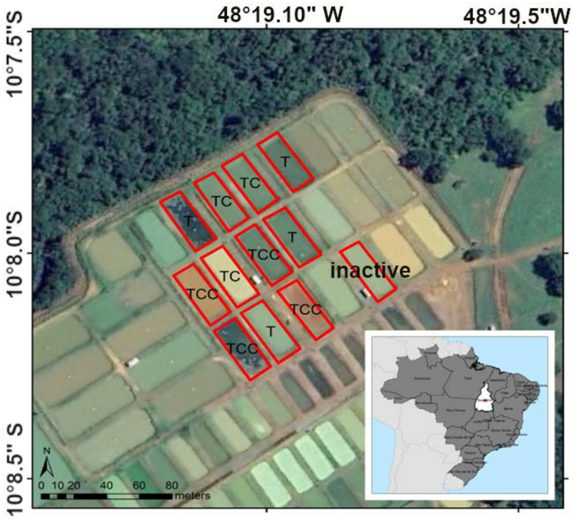

Figure 1. Experimental area of Embrapa Fish and Aquaculture, Palmas, Tocantins, TO, Brazil.

Assessed ponds had an average area of 600 m² and a depth of 1.5 m. Before introducing the fishes, ponds were treated with limed (200 g/m²) and fertilized (5 g of urea/m², 3 g of single superphosphate/m², and 10 g of rice bran/m²). Three production systems were tested, each with four replicates: T (Tambaqui, *Colossoma macropomum*), TC (Tambaqui and Curimbatá, *Prochilodus sp*), and TCC (Tambaqui, Curimbatá and Amazon shrimp, *Macrobrachium amazonicus*). Systems with only one species are classified as monoculture, while those with two or more species are considered Integrated Multi-Trophic Aquaculture (IMTA). One pond was left untreated for fish farming and served as the control (inactive) pond.

Above water radiometry was measured using an ASD FieldSpec 4 spectroradiometer, which measures radiance (L, $\mu W\ m^{-2} sr^{-1}$). The acquisition geometry was carefully designed to avoid shadows and sunglint contamination. Remote sensing reflectance (Rrs) was calculated according to Mobley [10]. To correct residual sunglint contamination, we used the Ruddick et al. [11] approach, recommended for turbid to very turbid waters. The in situ Rrs were simulated for PlanetScope's SuperDove bands (Rrs-Dove). The SuperDove has a spatial resolution of 3.7 m and eight spectral bands, making it suitable for assessing small fishponds.

Using the Rrs-Dove, we aimed to test which unsupervised classification algorithm performed best. We first normalized the Rrs-Dove by its integrated value [12] using the trapezoidal method over the 443-865 nm bands. We tested three different methods: i) Spectral Angle Mapper (SAM), ii) Euclidean distance and iii) Mahalanobis distance to classify the spectral curves.

SAM calculates the angular distance between two spectral curves, treating them as vectors in a high-dimensional space [13]. As the magnitude of the spectral curve is not taken into account, normalization is not strictly necessary. However, for consistency, we normalized all spectral curves before applying the methods. Euclidian distance measures the linear distance between two points in multidimensional space [14], while Mahalanobis distance is a statistical metric, that accounts for correlations between variables and scales the distance based on covariance structure of the data [15].

The turbidity (NTU) was measured using a turbidimeter (Hach 2100Q, Loveland, CO, USA), and chlorophyll-a was measured spectrophotometrically (Hach DR5000, Loveland, CO, USA) following the [16] protocol on water samples from the active ponds. In addition, the Normalized Difference Chlorophyll Index (NDCI) was calculated using equation 1 to assess the presence of phytoplankton based on the near-infrared (NIR – Band 705 nm) and red (Band 665 nm) bands of the Rrs-Dove data.

$$NDCI = \frac{NIR-RED}{NIR+RED} \quad (1)$$

3. RESULTS

Rrs-Dove spectral curves were measured throughout the entire production cycle of different fishponds. The average Rrs-Dove measured in active ponds (dark blue line, Figure 2) differs significantly from the average Rrs-Dove measured in inactive ponds (red dashed line, Figure 2). A clear discrepancy is observed between 665 and 705 nm (Figure 2).

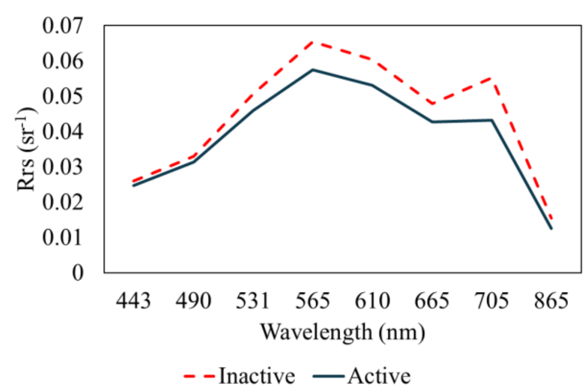

Figure 2. Average remote sensing reflectance of the inactive and active ponds.

The “inactive” and “active” spectral curves from Figure 2 were used as reference inputs for the classification algorithms. While all algorithms achieved good accuracy (>60%), Mahalanobis distance performed best with an overall accuracy of 83% (Table 1), followed by SAM with 77% and Euclidian distance with 62% (results not shown).

Both SAM and Mahalanobis distance correctly classified the inactive ponds, with 100% accuracy, whereas

Euclidian distance performed poorly in this category with an accuracy of only 29%. However, active ponds were more frequently misclassified as inactive by all methods. Given the superior performance of the Mahalanobis distance, its results are shown in Table 1. Active ponds were correctly classified 82% of the time, although IMTA ponds were more frequently misclassified as inactive, with an accuracy of 79%.

Mahalanobis Distance		
	Inactive Ponds	Active Ponds
Specificity and Recall	7/7 100%	62/76 82%
Total accuracy	**83%**	
F1-Score	**90%**	
Occupancy and Fish Culture		
Inactive	7/7	100%
IMTA	36/48	79%
Monoculture	24/28	86%

Table 1. Confusion Matrix and classification performance of Mahalanobis distance.

4. DISCUSSION

Our results indicate that the proposed unsupervised classification based on Mahalanobis distance performed well, achieving high recall and a good balance between precision and recall, as shown by the F1-score (Table 1). Nevertheless, thirteen out of 83 samples were misclassified as inactive (~15%), and we aim to understand the underlying reasons. We gathered all the misclassified Rrs-Dove spectral curves and observed that they were somewhat similar to the spectral curve of inactive ponds, indicating the presence of chla (Figure 3).

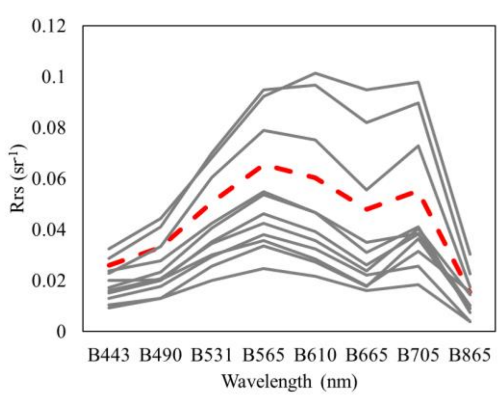

Figure 3. Remote sensing reflectance of the misclassified ponds. The dashed red line is the average of Rrs-Dove from inactive ponds.

We plotted water quality metrics (turbidity, chla, chla/turbidity ratio and NDCI, Figure 4) for both misclassified and correctly classified fishponds based on Mahalanobis distance. We observed higher variability in the misclassified fishponds, along with a significantly greater presence of chla. Unfortunately, we did not have water quality measurements for the inactive fishponds, so it was not possible at this moment to compare active, inactive and misclassified fishponds.

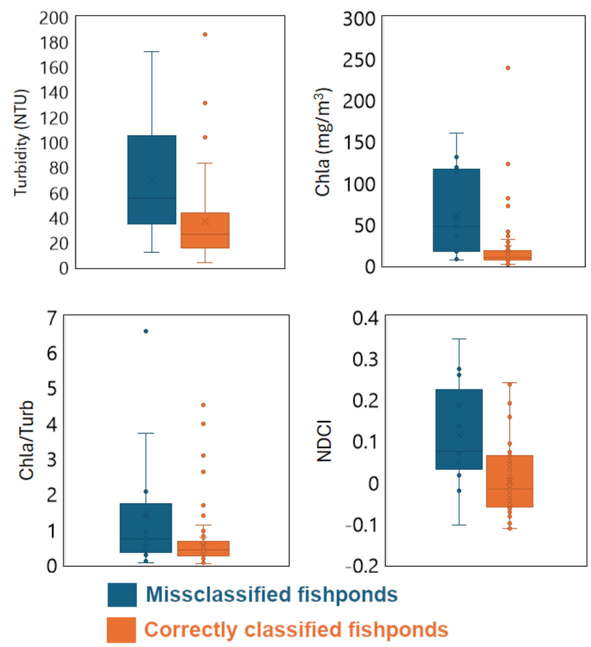

Figure 4. Boxplots of turbidity (NTU), chlorophyll-a concentration (mg/m³), chla-to-turbidity ratio, and NDCI in the ponds during the study period (Aug/23–Feb/24). The blue boxplots represent the misclassified fishponds, while the orange boxplots indicate the correctly classified fishponds according to Mahalanobis distance.

However, these parameters cannot fully explain all misclassified cases. Further studies are needed to assess phytoplankton dynamics, as these organisms can sink or float in response to variations in light availability, nutrient levels, water circulation, and pond temperature [17], as well as the presence of zooplankton that can pasture rapidly the phytoplankton [18–20], the concentration of colored dissolved organic matter affecting measurements [21], or even the ponds' previous use, to understand what was previously cultivated there.

Regardless of the number of errors, it is important to note that our method correctly classified all inactive ponds throughout the seven months of the production cycle, while only occasionally misclassifying some active ponds during the same period. Our results indicate that continuous monitoring can effectively distinguish between active and inactive ponds.

5. CONCLUSIONS

Our hypothesis that fishpond activity assessment is possible using water colour remote sensing was supported, successfully utilizing Rrs simulated for SuperDove PlanetScope bands. For future studies, we recommend conducting a detailed assessment of pond' bio-optical properties to better characterize the optical differences between active and inactive ponds. Additionally, we suggest expanding in situ data collection to include other fishponds with characteristics different from those of Embrapa's Experimental Centre used in this study. We also recommend validating these findings with SuperDove PlanetScope imagery in future research.

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ACKNOWLEDGMENTS

We thank the project "Carbon footprint and impacts of aquaculture expansion in the Amazon" (Amazon +10 Initiative / FAPESP (2022/10443-6) / FAPERO / FAPT) for funding this research. This work was partially financed by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior—Brazil (CAPES)—Finance Code 001, Agência Espacial Brasileira (AEB) and Instituto Nacional de Pesquisas Espaciais (INPE).