# SPECTRAL COMPARISON OF REMOTE SENSING REFLECTANCE IN FISHPONDS IN THE LEGAL AMAZONIA

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## ABSTRACT

Remote sensing has emerged as a promising tool for environmental monitoring, offering a synoptic view, which contrasts with the time-consuming and costly *in situ* measurements. This study compares hyperspectral, multispectral, and broadband remote sensing data collected from fishponds in Palmas, Tocantins State, using a combination of field measurements, satellite imagery from PlanetScope SuperDove and smartphone applications called Hydrocolor, respectively. Results showed significant correlations between longer wavelength bands, across different datasets. However, weaker correlations in shorter wavelengths suggest the need for periodic adjustments, especially for lower-spectral-resolution sensors. Additionally, limitations such as cloud cover in satellite imagery highlight the importance of multi-sensor approaches, integrating satellite data with smartphone-based monitoring, to track small water bodies. The findings highlight the potential of citizen science in environmental management, although challenges related to data validation across platforms remain. Further studies are required to improve data integration and promote the adoption of emerging technologies in water monitoring.

***Key words* —** Aquiculture, water color, amazonian fish farm, citizen science, Hydrocolor.

## 1. INTRODUCTION

Aquaculture has emerged as an important source of protein production, essential for food security and local economic growth [1]. With the growing demand for sustainable resources, especially in the Legal Amazon region, the expansion of this activity requires efficient monitoring tools to ensure water quality and productive performance.

Compared to *in situ* water quality monitoring, which is time-consuming and often costly, remote sensing has proven to be a solution for synoptic assessment of these parameters [2]. However, there are limitations to the use of this type of data, such as the need for periodic validation and the occurrence of cloud cover. The use of orbital data from the Planet constellation has become crucial in reducing data collection gaps, given its high revisit frequency and ability to cover extensive areas with high special resolution. To overcome limitations such as cloud cover, some alternatives have been proposed, such as the use of telemetry buoys, drones, and smartphone applications [3-5]. Specifically, the use of data generated by mobile applications has proven to be a democratic tool for real-time water quality monitoring, facilitating data collection and sharing by local producers [6]. The main limitations of this type of data include low spectral resolution, the variability in the spectral response function of each smartphone model, and the need of a reflectance standard.

The integration of these data into large databases enables the development of citizen science, allowing the community to actively participate in environmental monitoring and management. The integration of water quality monitoring tools can address these limitations with a multi-sensor approach [7]. The comparison and validation of these data, generated by conventional methods and new technologies is essential to ensure accuracy and reliability. Thus, comparing these different data sets is a challenge that must be addressed to promote the adoption of emerging technologies in water resource management. Therefore, the objective of this study is to compare data from different instruments used in the monitoring of fishponds in aquaculture.

## 2. MATERIAL AND METHODS

Data were collected at the Experimental Center (CEAQ) of Embrapa Fisheries and Aquaculture in Palmas, Tocantins State, Brazil (Figure 1). The work was conducted between August 2023 and February 2024 in ponds with a surface area of 600 m² and a depth of 1.5 m, used for fish farming. Species used in this study included Tambaqui (*Colossoma macropomum*), Curimbatá (*Prochilodus sp.*), and Amazon

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shrimp (*Macrobrachium amazonicum*) in an Integrated Multi-Trophic Aquaculture (IMTA) system.


**Figure 1: Study area at the Aquaculture Experimental Center (CEAQ) – Embrapa Fisheries and Aquaculture in Palmas, Tocantins State, Brazil.**

ASD FieldSpec 4 (350-2500 nm) instrument was operated in radiance mode to collect water leaving radiance (Lw), sky radiance (Lsky) and the radiance of a Lambertian plaque (Ls). The Ls was converted to irradiance by integrating over the hemisphere by multiplying by π to obtain remote sensing reflectance (Rrs) data. The Rrs, with a spectral resolution of 1 nm, was processed following Mobley [8] protocol with Ruddick et al. [9] scheme to correct residual sunglint contamination. Broadband remote sensing reflectance measurements were also taken using the Hydrocolor App (470 nm, 540 nm, and 600 nm) during fieldwork conducted on November 13, 2023, December 18, 2023, January 22, 2024, and February 21, 2024. Additionally, Planet constellation images (443 nm, 490 nm, 531 nm, 565 nm, 610 nm, 665 nm, 705 nm, and 865 nm) with 3.7 m of spatial resolution were used for November 13, 2023. Hyperspectral data were simulated in R and Matlab environments to compare the bands with multispectral and broadband data [10] using Root Mean Square Deviation (RMSD), Mean Relative Absolute Difference (MRAD), and Mean Bias (MB) as shown in Equations 1, 2, and 3 below.

$$\text{RMSD} = \left\{\frac{\sum_{i=1}^{n}\left[(log_{10}(y_i) - log_{10}(x_i))\right]^2}{n}\right\}^{\frac{1}{2}} \quad [1]$$

$$\text{MRAD} = \frac{1}{\text{N}} \text{ X } \frac{\sum_{i}^{n} |(y_i) - (x_i)|}{(x_i)} \text{ X } 100\% \quad [2]$$

$$\text{MB} = \frac{1}{\text{N}} \text{ X } \sum_{i=1}^{n} |log_{10}(y_i) - log_{10}(x_i)| \quad [3]$$

Where $x_i$ is the *in situ* Rrs and $y_i$ is the simulated Rrs from these instruments.

## 3. RESULTS

The different configurations of each type of Rrs sampling have strengths and limitations, which are summarized in Table 1.

| Sensor | Main Quality | Main Limitation | Spectral Bands |
|---|---|---|---|
| ASD FieldSpec | Field truth | Requires experience for data collection | 350-2500 nm |
| Hydrocolor App | Democratic technology | Coarse spectral resolution | 470 nm, 540 nm, and 600 nm |
| Planet | Spatial and temporal resolution | Requires cloud-free conditions | 443 nm, 490 nm, 531 nm, 565 nm, 610 nm, 665 nm, 705 nm, and 865 nm |

**Table 1: Comparison of the main attributes of the sensors used.**

The comparison of the data simulated through hyperspectral reflectance with ASD FieldSpec 4 is organized in Figure 2, where A is the comparison with Planet data, B is the comparison with Hydrocolor data, and C is the comparison between Planet and Hydrocolor data. The results of the statistics of the spectral band comparison are organized in Table 2.

| | Band | $R^2$ | RMSD | Slope | Intercept | MB | MRAD | N |
|---|---|---|---|---|---|---|---|---|
| **FS X PD** | 443 | 0.72 | 0.15 | 0.242 | 0.013 | 0.11 | 24 | 15 |
| | 490 | **0.91** | 0.13 | 0.294 | 0.015 | **0.10** | 23 | 15 |
| | 531 | 0.79 | 0.12 | 0.329 | 0.030 | **0.10** | 27 | 15 |
| | 565 | 0.86 | 0.14 | 0.384 | 0.040 | 0.12 | 34 | 15 |
| | 610 | 0.84 | 0.23 | 0.404 | 0.048 | 0.21 | 68 | 15 |
| | 665 | 0.88 | 0.33 | 0.510 | 0.047 | 0.29 | 11 | 15 |
| | 705 | 0.80 | 0.41 | 0.509 | 0.070 | 0.37 | 16 | 15 |
| | 865 | 0.86 | 1.31 | 1.02 | 0.177 | 1.26 | 228 | 15 |
| **FS X HC** | 470 | 0.43 | 0.31 | 0.433 | 0.003 | 0.27 | 44 | 54 |
| | 540 | 0.54 | 0.27 | 0.504 | 0.004 | 0.23 | 40 | 54 |
| | 600 | 0.64 | 0.26 | 0.550 | 0.003 | 0.22 | 39 | 54 |
| **HC X PD** | 470 | 0.86 | 0.34 | 1.21 | 0.010 | 0.33 | 118 | 14 |
| | 540 | 0.72 | 0.38 | 1.05 | 0.024 | 0.37 | 142 | 14 |
| | 600 | 0.82 | 0.50 | 1.31 | 0.038 | 0.49 | 223 | 14 |

**Table 2: Comparison of statistical metrics between samples from different sensors. ASD Fieldspec 4 (FS) data were simulated into multispectral data from PlanetScope's SuperDove CubeSat data (PD) and broadband data from Hydrocolor application (HC).**

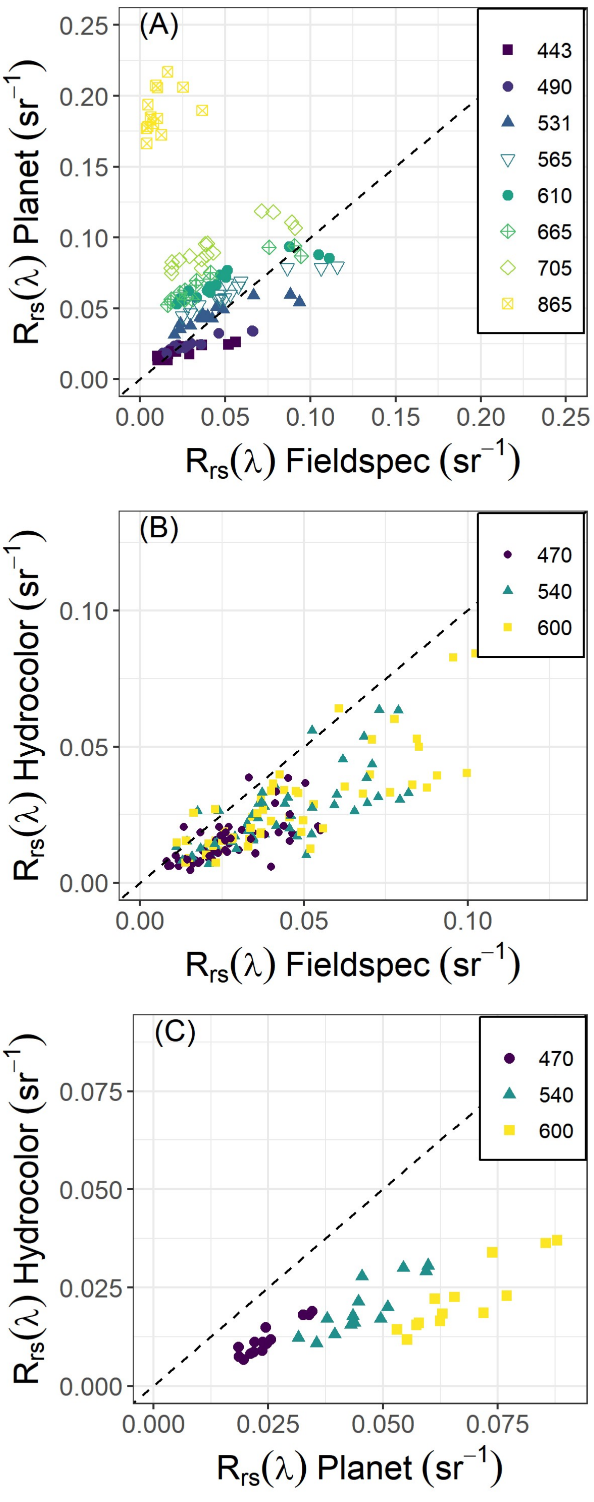


**Figure 2: Scatterplots of Rrs match-ups.**

The comparison between ASD Fieldspec 4 and Planet sensors across various bands demonstrates strong correlations, with $R^2$ values ranging from 0.72 to 0.92 for visible wavelengths and slightly decreasing in the near-infrared region. ASD Fieldspec 4 dataset is closely related to Planet dataset, particularly at 490 nm ($R^2 = 0.92$) and 665 nm ($R^2 = 0.89$), indicating high consistency in measuring Rrs in these ranges. However, increasing RMSD values at longer wavelengths suggest more significant variability, mostly at 865 nm (RMSD = 1.32).

The comparison between ASD Fieldspec 4 and Hydrocolor show lower correlations, with $R^2$ values ranging from 0.43 to 0.64, particularly struggling in the blue band ($R^2 = 0.43$). In contrast, the Hydrocolor and Planet sensor comparison yields high consistency across all measured wavelengths, with $R^2$ values exceeding 0.73, particularly in the red band ($R^2 = 0.83$). Although this comparison demonstrates good agreement, it shows a higher bias compared to the other comparisons. The results highlight strong agreement between the orbital and *in situ* sensors, suggesting that either can be reliably used for reflectance measurements. However further investigation into the discrepancies in the near-infrared bands is necessary.

## 4. DISCUSSION

The main limitation of orbital remote sensing is the need for favorable atmospheric conditions, as the presence of clouds in the scene prevents the use of this type of data. Even using the Planet constellation image bank, which offers daily revisits and a spatial resolution of 3 meters necessary for studying small targets, such as ponds for fish farming, Table 2 resulted in a reduced sample size (N) compared to other instruments. Considering the size of the ponds, the adjacency effect is inevitable. This can be observed in the high values of longer wavelength bands, like in Figure 2 A, in the 865 band (even when using pixels from the center of the ponds), which are contaminated by the surrounding soil signal.

Another characteristic observed in fishponds is the daily high spectral variation, where factors such as stocking type, stocking density, chlorophyll-a concentration, and/or the presence of macrophytes can change the water color throughout the day. This presents an additional challenge for integrated data collection among instruments.

The accuracy of the data obtained by the Planet satellite is a fundamental issue in validating the use of remote sensing in aquaculture. In the context of studies in small areas, such as ponds for fish farming, the spatial resolution of the planet and the frequency of daily revisits have significant advantages. However, the precision of the Rrs depends on factors such as solar angle and cloud presence, which can interfere with the quality of the obtained data. It is also important to note that *in situ* data may also contain inherent variability in the data collection process, even with all correction procedures. Comparing the reflectance data from Planet with field data, we observed a close relationship for longer wavelength bands, especially in the red bands. Notably, the comparison between ASD Fieldspec data and Planet data showed the smallest biases (Table 2), suggesting sufficient accuracy for temporal pond monitoring, though occasional corrections are needed due to adjacency effects.

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The coefficient of determination measures the linear relationship between datasets and serves as this study's primary sensor comparison tool. It is possible to observe that the relationship between the shorter wavelength-centered bands is weaker compared to the longer wavelength-centered spectral bands (in all cases, the red band showed the best correlation between the datasets). The best correlations occurred between the Planet data and the other sensors, likely due to the reduced sample size (Table 2). The comparison between the Hydrocolor app data and the ASD Fieldspec data showed the weakest correlation. This may indicate the need for different corrections in the hyperspectral data regarding the presence of glint, a common artifact in radiometric data. Additionally, the simulation of the bands from the Fiedlspec to RGB bands of the smartphone camaras adopted the response functions from the literature [10] and not from the model of smartphone actually used on the Hydrocolor sampling, which is potentially adding more uncertainty in this comparison. These results are consistent with findings from other studies, further supporting the reliability of these observations in sensor comparisons [5,6].

The proposed methodology shows great potential to expand the use of remote sensing data in aquaculture systems in the Amazon and other regions with highly turbid water bodies. By integrating orbital, hyperspectral, and app data, it is possible to build a robust database that can optimize and popularize the monitoring of essential environmental variables and improve pond management. This process also contributes to citizen science, as low-cost tools like mobile applications allow for accessible and continuous data collection. This methodology represents an advancement in sustainable water resource management for aquaculture, with the potential for adaptation to other areas sensitive to rapid environmental changes and locations where conventional monitoring is unfeasible.

## 5. CONCLUSIONS

This study demonstrated the advantages and limitations of different sensors to monitor ponds in the Legal Amazon. Hyperspectral, multispectral, and broadband data showed significant correlation, particularly in longer spectral bands, such as red and near-infrared. However, lower correlation in shorter wavelengths underlines the importance of periodic adjustments and validations, especially with lower-resolution sensors like the Hydrocolor app, which require a gray reference panel for accurate data - a limitation for widespread citizen science application. Nevertheless, studies like this are essential for creating and validating useful algorithms for monitoring parameters like turbidity, chlorophyll-a and suspended particulate matter (SPM), which present challenges in extremely turbid waters.

The need for favorable atmospheric conditions also limits the continuous use of satellite remote sensing data, reinforcing the value of multi-sensor approaches, including smartphones, for monitoring small water bodies like ponds. Citizen science shows promising potential, yet data validation across sources remains a challenge. Future research should expand on using diverse sensors and satellite data to enhance monitoring scalability. Additionally, exploring daily variations in remote sensing reflectance (Rrs) could identify optimal times for data collection. Testing these techniques in varied environments and aquaculture systems will further support large-scale application, advancing environmental management and monitoring practices.

## 6. REFERENCES


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