Chlorophyll-a and Turbidity estimation using UAV imagery and machine learning in a tropical eutrophic reservoir

Daniel H. C. Salim[1], Caio C. S. Mello[2], Gabriel Pereira[3], Raian V. Maretto[4], Frederico Santos Machado[5], Camila C. Amorim[6]

[1] Dept. of Sanitary and Environmental Engineering, Universidade Federal de Minas Gerais, Brazil – danielhcsalim@ufmg.br
[2] Dept. of Sanitary and Environmental Engineering, Universidade Federal de Minas Gerais, Brazil – caiocsm@ufmg.br
[3] Department of Geosciences, Universidade Federal de São João del-Rei, Brazil - pereira@ufsj.edu.br
[4] Faculty of Geo-Information Science and Earth Observation, University of Twente, the Netherlands - r.v.maretto@utwente.nl
[5] Petrobras Research Center, Petróleo Brasileiro S.A. (Petrobras), Brazil - fredericomachado@petrobras.com.br
[6] Dept. of Sanitary and Environmental Engineering, Universidade Federal de Minas Gerais, Brazil - camila@desa.ufmg.br

Keywords: machine learning, UAV, chlorophyll-a, turbidity, water quality, eutrophic reservoir

Abstract

Unmanned Aerial Vehicles (UAVs) equipped with multispectral sensors offer a promising approach for monitoring water quality in optically complex inland waters, particularly in tropical eutrophic systems. This study investigates the performance of two UAV-mounted sensors, DJI Phantom 4 Multispectral and MicaSense RedEdge-P Dual, for estimating chlorophyll-a and turbidity concentrations in the Ibirité Reservoir, Brazil. Four UAV campaigns were conducted in 2024, alongside in situ measurements, and six regression models were evaluated. Results show that chlorophyll-a was robustly predicted using ensemble algorithms, with the MicaSense sensor achieving the best performance ($R^2 = 0.867$, RMSE = 6.72 μg/L). Turbidity estimation was more variable, with linear regression outperforming complex models when using MicaSense data ($R^2 = 0.712$). The DJI sensor consistently underperformed, mainly due to limited spectral resolution. Findings highlight the critical roles of sensor configuration, spectral sensitivity, and model selection in UAV-based water quality assessment.

1. Introduction

Unmanned Aerial Vehicles (UAVs) equipped with optical sensors have increasingly become integral to water quality monitoring, offering a complementary or alternative approach to conventional field sampling and satellite-based remote sensing. Their ability to acquire higher spatial resolution imagery on demand, at low operational cost, and with high temporal flexibility renders them particularly useful in small or dynamic inland water bodies. UAVs facilitate fine-scale assessments that capture spatial heterogeneity in limnological parameters—something often overlooked in traditional discrete sampling or limited by the spatial resolution of satellite platforms.

Among the water quality parameters of interest, chlorophyll-a and turbidity are commonly used as proxies for primary productivity and suspended matter concentration, respectively. Chlorophyll-a, a photosynthetic pigment found in phytoplankton, serves as a crucial indicator of trophic status and levels of eutrophication (Castro et al., 2020). Turbidity, on the other hand, measures the attenuation of light due to suspended particulate matter, including sediment, detritus, plankton, and organic material (Souza et al., 2023). Both parameters are vital for understanding ecological dynamics in lentic systems, influencing primary production, oxygen dynamics, and habitat suitability for aquatic organisms. As a result, their remote estimation holds significant importance for effective monitoring, early warning, and ecosystem management.

The optical behaviour of these parameters forms the scientific foundation for their retrieval via remote sensing. Chlorophyll-a exhibits characteristic absorption in the blue and red spectral regions, while reflecting in the green and red-edge portions of the spectrum. Turbidity, influenced primarily by the backscattering properties of suspended particles, tends to manifest increased reflectance in the visible and near-infrared regions depending on particle size, composition, and water depth. The ability to detect these spectral signals using multispectral UAV sensors depends not only on the spectral and radiometric configuration of the sensor but also on transient environmental conditions that alter water surface reflectance. Factors such as wind-induced surface roughness (waves), sun glint, cloud shading, and cloud glint can introduce significant variability in the measured reflectance, potentially masking the spectral signatures of chlorophyll-a and turbidity and complicating model calibration and validation. These effects are particularly relevant in small or shallow inland waters, where surface conditions can change rapidly during a single UAV flight (Salim et al., 2024). Consequently, the accuracy and reliability of empirical models depend on both data characteristics and environmental conditions.

Empirical modelling of chlorophyll-a and turbidity using UAV-based multispectral imagery has shown promising yet contrasting results for different parameters. Castro et al. (2020) employed a MicaSense RedEdge sensor to estimate chlorophyll-a in a eutrophic reservoir and reported high predictive performance, with the three-band algorithm reaching $R^2 = 0.812$ and the two-band algorithm $R^2 = 0.791$. Simpler indices like SABI and NDCI also performed well, achieving $R^2 = 0.781$ and $R^2 = 0.752$, respectively. In contrast, turbidity estimation showed weaker results, with the best UAV-based model using a green/red band ratio reaching only $R^2 = 0.547$. This performance gap highlights the greater spectral separability of chlorophyll-a and the difficulty of isolating turbidity signals in optically complex waters.

Although UAVs are increasingly used for water quality monitoring, few studies have directly compared different UAV-mounted multispectral sensors under the same environmental conditions, particularly in tropical eutrophic reservoirs, where optical complexity poses significant challenges (Burket et al., 2023; Pahlevan et al., 2021). Most existing research focuses on a single sensor or modelling approach, limiting our understanding of which combinations of sensor and model yield the most reliable results. Furthermore, there is limited evidence on whether advanced machine learning techniques consistently outperform simpler statistical models, such as linear regression, in these settings. This knowledge gap makes it difficult to design practical, cost-effective UAV-based monitoring strategies that balance sensor performance, model complexity, and operational feasibility.

This study addresses these gaps by systematically comparing two multispectral UAV sensors—DJI Phantom 4 Multispectral and MicaSense RedEdge-P Dual —for estimating chlorophyll-a and turbidity concentrations in a tropical eutrophic reservoir. Using data from four UAV campaigns and corresponding in situ measurements, we trained and evaluated six regression models, ranging from statistical (linear and exponential) to machine learning methods (decision tree, random forest, support vector regression, and XGBoost). We aim to assess how sensor configuration and model selection influence prediction accuracy and to offer practical guidance for the use of UAV-based remote sensing in inland water quality assessment.

2. Study Area and Field Data Acquisition

This study was conducted at the Ibirité Reservoir, situated in the metropolitan region of Belo Horizonte, Minas Gerais, Brazil. The reservoir encompasses an area of approximately 200 hectares. It represents a typical urban eutrophic system, subject to rapid water quality variations influenced by precipitation events, seasonal dynamics, urban runoff, and internal biogeochemical processes. These conditions contribute to a spatially and temporally heterogeneous optical environment, posing challenges for monitoring but offering a relevant context for testing high-resolution remote sensing techniques. In this regard, the Ibirité Reservoir provides an appropriate case study for evaluating the capacity of UAV-based multispectral imaging to retrieve limnological parameters in optically complex tropical inland waters. Figure 1 illustrates the location of the study area along with the georeferenced water sampling points employed in this research.

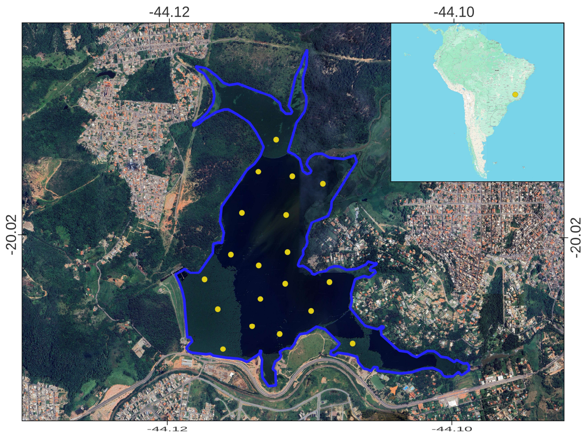

Figure 1. Study area and sampling locations at the Ibirité Reservoir, where UAV images and in situ measurements of turbidity and chlorophyll-a were collected

Four field campaigns were conducted across the transition from dry to wet season in 2024 (August 23, September 17, October 2, and November 6), capturing a range of hydrological and atmospheric conditions. To minimize sun glint effects during data acquisition, all UAV flights were scheduled in the early morning (between 08:00 and 10:30 AM) and solar elevation angles ranging between 25 and 45 degrees (Salim et al., 2024). Each field campaign was designed to ensure spatial alignment between UAV imagery and in situ measurements. The UAV followed a pre-programmed waypoint flight plan over georeferenced sampling locations, and water quality measurements were subsequently collected by boat at the same coordinates within a maximum interval of one hour. This approach allowed for the integration of near-simultaneous reflectance data and field observations, while maintaining operational efficiency and spatial precision.

Water samples were collected at 19 georeferenced locations distributed throughout the reservoir, covering nearshore and pelagic zones as well as areas with visible water quality gradients. At each station, a YSI ProDSS multiparameter probe was used to record chlorophyll-a concentration (in mg/L) and turbidity (in NTU) approximately 10–20 cm below the surface, minimizing surface reflectance artifacts while capturing the photic layer. All sampling locations were integrated into the UAV flight plans and image analysis pipeline, forming the ground truth dataset for regression modeling. On each campaign day, the field team aimed to visit all 19 stations, which were distributed across the reservoir according to accessibility, limited in some areas by the presence of dense aquatic vegetation. A total of 64 points were selected for regression analysis using MicaSense imagery and 67 points using DJI Phantom 4 Multispectral imagery, considering the availability of both in situ data and coincident UAV images.

Two multispectral UAV imaging platforms were deployed. The DJI Phantom 4 Multispectral is an integrated drone equipped with five sensors (450, 560, 650, 730 and 840 nm) and an RGB camera, capturing images at a native spatial resolution of ~6 cm/pixel at 100 m above ground altitude. The MicaSense RedEdge-P Dual is a dual-sensor configuration, capturing ten bands (centered at 444, 475, 531, 560, 650, 668, 705, 717, 740, and 842 nm) with images of 5 cm/pixel at 100 m above ground altitude. Multispectral imagery was radiometrically calibrated using Agisoft Metashape Professional (v2.2.0), following the official MicaSense guidelines for the RedEdge-P Dual sensor. Raw digital numbers (DNs) were first converted to spectral radiance using sensor-specific parameters, including exposure time, electronic gain, vignetting correction, and black level adjustment. A reflectance calibration step was then conducted using a calibrated reflectance panel (CRP) imaged prior to each flight. For each band of the MicaSense RedEdge-P Dual, a reflectance factor was derived by comparing the measured radiance over the CRP to its known reflectance values. These factors were subsequently applied to the radiance imagery to generate accurate surface reflectance, ensuring consistency across bands and flight campaigns.

To construct the modelling dataset, median reflectance values from each spectral band were extracted at the georeferenced sampling locations. These spectral metrics were then integrated with the corresponding in situ measurements of turbidity and chlorophyll-a, providing the predictor and response variables for subsequent regression analysis. The resulting spectral signatures, shown in Figure 2, exhibit distinct peaks in the green and red-edge regions, with lower reflectance in the blue, red, and near-infrared bands. This pattern is characteristic of eutrophic waters dominated by phytoplankton, closely resembling the spectral responses observed in Halstead's Bay, Lake Minnetonka (Burket et al., 2023). Similar spectral features have also been reported for Optical Water Types (OWT) 5 and 6, which are associated with high concentrations of different phytoplankton blooms and elevated turbidity levels (Pahlevan et al., 2021).

During the study period, water quality in the Ibirité Reservoir was characterized by dominant, elevated chlorophyll-a concentrations (median = 55.1 mg/L; standard deviation = 19.6 mg/L) and moderate turbidity levels (median = 11.4 NTU; standard deviation = 4.4 NTU). NTU stands for Nephelometric Turbidity unit.

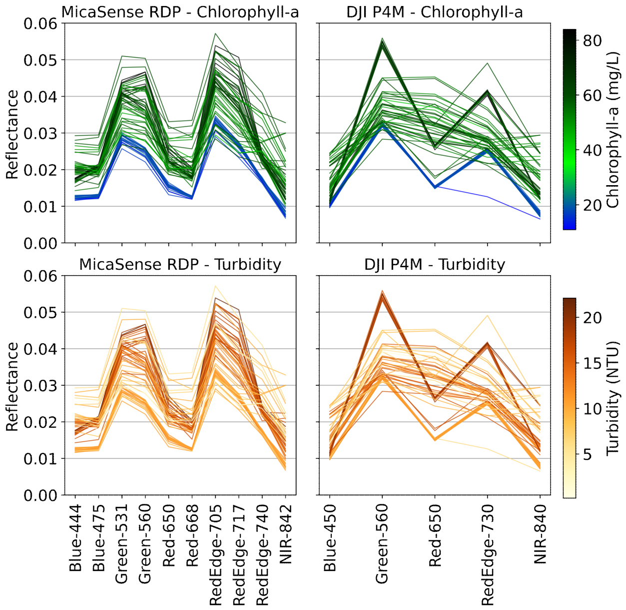

Figure 2. Spectral Signatures for Chlorophyll-a and Turbidity Using UAV Sensors

4. Machine Learning and Statistical Modelling Workflow

To explore the predictive potential of UAV-derived reflectance for water quality estimation, Pearson correlation coefficients were first calculated between each spectral band and the in situ limnological variables (chlorophyll-a and turbidity). This initial step provided insight into spectral sensitivity and informed the subsequent modeling approach. Six regression models were then evaluated to capture a range of relationships between reflectance and water quality parameters: Linear Regression, Exponential Regression, Decision Tree, Random Forest, Support Vector Regression with Radial Basis Function kernel (SVR-RBF), and Extreme Gradient Boosting (XGBoost).

A stratified 5-fold cross-validation scheme was applied to ensure robust model evaluation, maintaining balanced distributions of target values across folds. Model performance was assessed using the coefficient of determination (R^2) and root mean square error (RMSE), which respectively represent the proportion of variance explained and the dispersion of prediction errors.

For each combination of sensor and target variable, the best-performing model was selected based on average cross-validation scores and then retrained using the full dataset to produce the final predictive function. This workflow enabled a comparative assessment of modeling strategies across different sensor configurations and target parameters, examining the relationship between algorithmic complexity and the stability of predictions across multiple sampling campaigns.

3. Results

3.1 Chlrophyll-a

The spectral correlation analysis demonstrated a consistent and interpretable pattern for chlorophyll-a detection across both UAV platforms. As shown in Figure 3 (a–b), Spearman correlation coefficients indicated a strong sensitivity of chlorophyll-a to the green and red-edge spectral regions. For the MicaSense RedEdge-P Dual sensor, the highest correlations were found at 560 nm (r = 0.766), 531 nm (r = 0.735), and 717 nm (r = 0.730), all of which align with known reflectance features of chlorophyll-a in optically active waters. The DJI Phantom 4 Multispectral sensor exhibited a similar spectral response, with peak correlations at 560 nm (r = 0.613) and 730 nm (r = 0.632). These results align with previous studies highlighting the importance of red-edge wavelengths for detecting chlorophyll-a, particularly in productive inland waters with elevated phytoplankton biomass (Castro et al., 2020). The stronger correlations observed with the MicaSense sensor are likely due to its narrower spectral bands and the use of a calibrated reflectance panel (CRP) specifically optimized for that sensor, enhancing radiometric accuracy and spectral sensitivity.

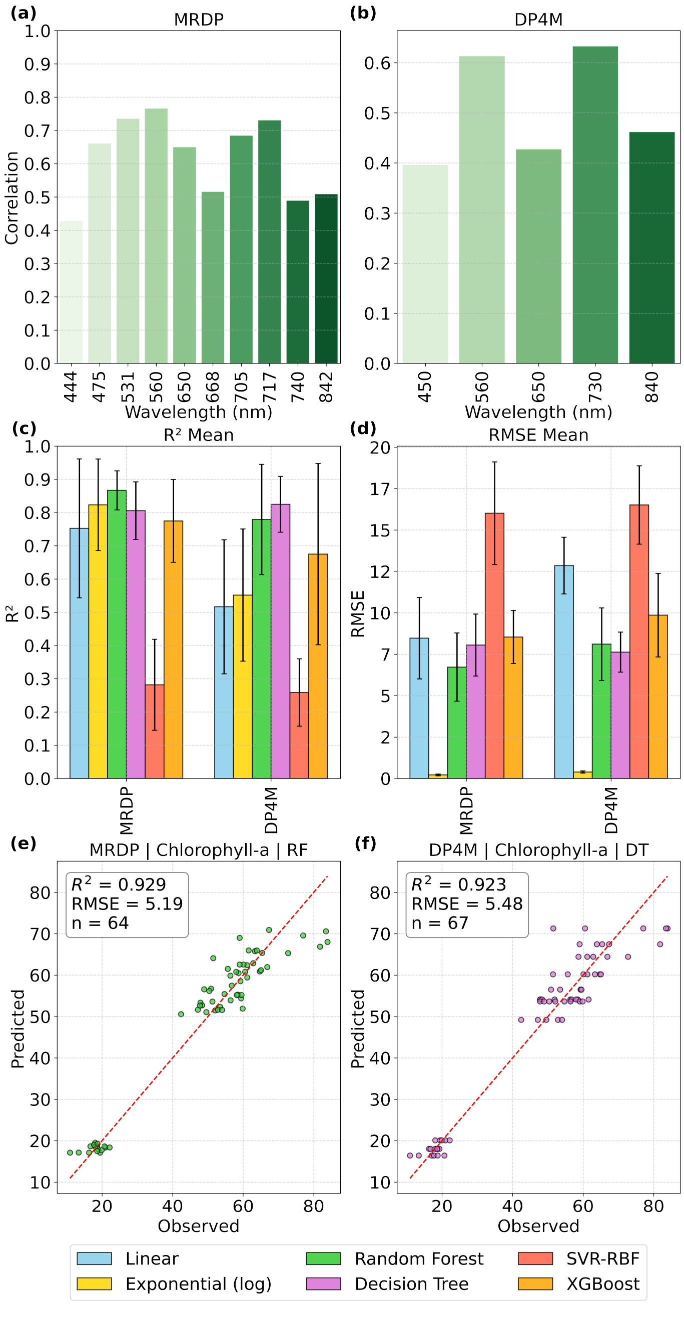

Figure 3. Sensor-specific performance and spectral sensitivity analysis for chlorophyll-a retrieval using machine learning models. Panels show: (a–b) Spearman correlations across spectral bands, (c–d) model accuracy metrics (R^2 and RMSE), and (e–f) regression plots for the MicaSense RedEdge-P Dual (MRDP) and DJI P4M platforms.

Regarding model performance, shown in Figure 3 (c–d), substantial differences were observed across sensors and algorithms. For the MicaSense sensor, the RF model achieved the highest predictive accuracy ($R^2 = 0.867$; RMSE = 6.72 µg/L), followed by the exponential regression ($R^2 = 0.823$) and DT ($R^2 = 0.806$) models. Conversely, the SVR-RBF model performed poorly ($R^2 = 0.282$), indicating limited generalizability for chlorophyll-a retrieval under these conditions. For the DJI P4M, the DT model yielded the best results ($R^2 = 0.825$; RMSE = 7.63 µg/L), followed by RF ($R^2 = 0.779$), while SVR-RBF again showed the weakest performance ($R^2 = 0.258$). These results highlight the robustness of ensemble and tree-based algorithms in capturing the non-linear relationship between chlorophyll-a and reflectance in eutrophic waters. Similar performance levels have been reported in previous studies. Castro et al. (2020) achieved R^2 values up to 0.94 using a MicaSense RedEdge sensor imagery to estimate chlorophyll-a, while Xiao et al. (2023) reported $R^2 = 0.69$ using the DJI P4M, reinforcing the better performance of Micasense.

Scatterplots of observed versus predicted values further confirmed these findings (Figure 3 (e–f)), revealing tight clustering around the 1:1 line and minimal dispersion, indicative of strong model generalization.

3.2 Turbidity

Turbidity estimation based on spectral reflectance exhibited more complex and less predictable patterns compared to chlorophyll-a. As shown in Figure 4 (a–b), Spearman correlation values were generally lower and more variable across the spectral range, reflecting the diffuse nature of turbidity-related optical signals. For the MicaSense RedEdge-P Dual sensor, moderate positive correlations were observed in the red-edge region, r = 0.541 at 717 nm and r = 0.502 at 705 nm, followed by weaker, yet still positive, correlations in the green spectral range (e.g., 560 nm, r = 0.427). In contrast, the DJI P4M exhibited overall lower spectral sensitivity to turbidity, with its highest correlations also located in the green (560 nm, r = 0.453) and red-edge (730 nm, r = 0.422) bands. These trends are consistent with Xiao et al. (2023), who reported a strong correlation between suspended solids and the red band (r = 0.67), highlighting the band's sensitivity to backscattering by particulate matter. Additionally, their study found that the spectral index (RE − G)/(RE + G) was among the most effective for turbidity retrieval, achieving a correlation of r = 0.63. This aligns well with our own results, where both green and red-edge bands emerged as most informative.

Interestingly, negative correlations were also observed, particularly in the blue, red and near-infrared regions, likely due to overlapping effects of chlorophyll, coloured dissolved organic matter (CDOM), and organic particles in optically complex waters (Pahlevan et al., 2021). When models were trained using only bands with positive correlations, predictive performance declined consistently (data not shown).

Regression modeling revealed clear differences in turbidity estimation performance between sensors and algorithms (Figure 4c–f). For the MicaSense RedEdge-P Dual, Linear Regression consistently produced the best results, with a mean R^2 of 0.712 and RMSE of 2.22, outperforming more complex models such as RF, DT, and SVR-RBF, which yielded lower R^2 values (0.577–0.616) and higher RMSEs. This outcome challenges the notion that nonlinear approaches inherently perform better in optically complex inland waters. In contrast, all models performed poorly with the DJI P4M, whose five-band configuration offered limited spectral sensitivity to turbidity. The best-performing algorithm, SVR-RBF, achieved only $R^2 = 0.285$ and RMSE = 3.25, indicating restricted capacity to capture relevant backscattering signals. Comparable challenges in turbidity modeling were reported by Cui et al. (2022), who applied RF and SVF to Sentinel-2 and HJ-1A/B satellite data over Lake Chaohu, achieving R^2 values of 0.67 (RF) and 0.60 (SVR), despite the broader spectral coverage of the sensors. Similarly, Dias et al. (2021) employed Micasense imagery to estimate total suspended solids in the Guarapiranga Reservoir, and reported R^2 values of 0.78 (RF), 0.75 (SVM), and 0.72 (multiple linear regression). These results are consistent with or slightly higher than the performance obtained with the MicaSense RedEdge-P Dual sensor in the present study, and substantially outperform those from the DJI P4M.

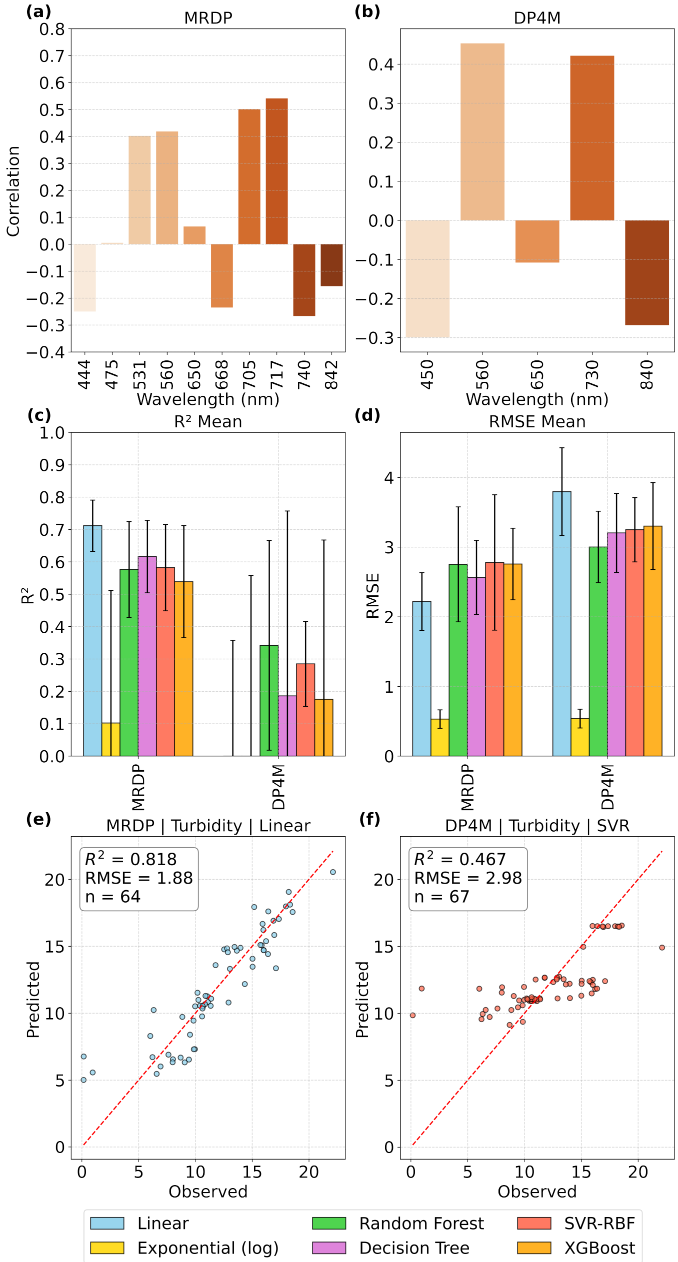

Figure 4. Sensor-specific performance and spectral sensitivity analysis for turbidity retrieval using machine learning models. Panels show: (a–b) Spearman correlations across spectral bands, (c–d) model accuracy metrics (R^2 and RMSE), and (e–f)

regression plots for the MicaSense RedEdge-P Dual (MRDP) and DJI P4M platforms.

These findings underscore how sensor limitations, overlapping spectral influences (e.g., phytoplankton and CDOM), and the diffuse nature of turbidity constrain model performance, regardless of algorithmic complexity. Consequently, sensor selection and waterbody characteristics must be jointly considered in UAV-based turbidity retrievals, beyond model tuning alone.

4. Conclusions

This study systematically evaluated the capacity of UAV-mounted multispectral sensors, in combination with statistical and machine learning models, to retrieve key limnological indicators—chlorophyll-a and turbidity—in a tropical eutrophic reservoir. The results demonstrated robust predictive capabilities for chlorophyll-a, particularly when leveraging ensemble-based models such as Random Forests and decision trees. The MicaSense RedEdge-P Dual sensor consistently outperformed the DJI Phantom 4 Multispectral platform, achieving higher spectral sensitivity and improved model accuracy (R^2 = 0.867 vs. 0.825, respectively). In contrast, turbidity estimation exhibited lower and more variable performance, with the best results (R^2 = 0.712) emerging from linear regression models using MicaSense data. These discrepancies underscore the differential spectral expressiveness of the two parameters and the inherent challenges associated with turbidity retrieval in optically complex waters.

The superior performance of chlorophyll-a models is attributable to the distinct spectral absorption and reflectance features of this pigment, particularly within the green and red-edge regions, which are well captured by the MicaSense sensor's narrowband configuration. Moreover, the inclusion of radiometric calibration using a reflectance panel substantially enhanced the reliability of surface reflectance estimates. In contrast, turbidity exhibits broader and more diffuse spectral signatures, often overlapping with other water constituents. This optical ambiguity limits the discriminative power of multispectral sensors, particularly those with fewer bands and lower spectral specificity, such as the DJI P4M.

From a methodological standpoint, the results challenge the assumption that advanced machine learning algorithms always outperform simpler models in remote sensing applications. While ensemble and tree-based approaches proved highly effective for chlorophyll-a estimation, linear regression models outperformed more complex algorithms in the case of turbidity, particularly when using MicaSense data. These findings suggest that model selection should be parameter-specific and guided by the underlying spectral structure of the data. Furthermore, they underscore the importance of harmonizing sensor selection, radiometric processing, and algorithmic complexity in the design of UAV-based water quality monitoring systems. Operational factors, such as flight planning, sun angle optimization, and timing relative to hydrological events, also played a critical role in ensuring the consistency of reflectance measurements and minimizing noise.

Future research should aim to expand the temporal scope of UAV campaigns to cover a complete hydrological year, thereby capturing the full range of seasonal and intra-annual variability in limnological conditions. Integrating UAV data with satellite observations—particularly from high-resolution platforms such as Sentinel-2—would enhance spatial and temporal coverage and allow for multiscale modelling approaches. Moreover, the application of advanced machine learning techniques, including deep learning architectures, holds promise for improving the retrieval of complex parameters such as turbidity and for expanding the scope of analysis to additional water quality indicators, such as phycocyanin. Finally, the integration of optical modelling, UAV-satellite fusion, and long-term in situ validation will be essential for developing scalable, adaptive monitoring frameworks that can inform real-time decision-making and ecosystem management in tropical inland waters.

5. Acknowledgments

The authors acknowledge Petrobras/ANP for supporting the AQUASMART Research and Development Project, under which this study was conducted. We also thank the technical staff and colleagues involved in data collection and processing, as well as the Universidade Federal de Minas Gerais (UFMG) for equipment and logistical support. Additional support was provided by the Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPq), Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES), and Fundação de Amparo à Pesquisa do Estado de Minas Gerais (FAPEMIG).

References

Burket, M.O., Olmanson, L.G., Brezonik, P.L., 2023. Comparison of Two Water Color Algorithms: Implications for the Remote Sensing of Water Bodies with Moderate to High CDOM or Chlorophyll Levels. Sensors 23. https://doi.org/10.3390/s23031071

Castro, C., Gómez, J.A., Martín, J., Sánchez, B.A., Arango, J.L., Tuya, F.A., Diaz-Varela, R.A., 2020. An UAV and Satellite Multispectral Data Approach to Monitor Water Quality in Small Reservoirs. Remote Sens. 12, 1–33. https://doi.org/https://doi.org/10.3390/rs12091514

Cui, M., Sun, Y., Huang, C., Li, M., 2022. Water Turbidity Retrieval Based on UAV Hyperspectral Remote Sensing. Water (Switzerland)14.https://doi.org/10.3390/w14010128

Dias, R.L.S., da Silva, D.D., Fernandes-Filho, E.I., do Amaral, C.H., dos Santos, E.P., Marques, J.F., Veloso, G.V., 2021. Machine learning models applied to TSS estimation in a reservoir using multispectral sensor onboard to RPA. Ecol. Inform. 65. https://doi.org/10.1016/j.ecoinf.2021.101414

Pahlevan, N., Mangin, A., Balasubramanian, S. V., Smith, B., 2021. ACIX-Aqua: A global assessment of atmospheric correction methods for Landsat-8 and Sentinel-2 over lakes, rivers, and coastal waters. Remote Sens. Environ. 258. https://doi.org/10.1016/j.rse.2021.112366

Salim, D.H.C., Andrade, G.R., Assunção, A.F., Cosme, P.H. de M., Pereira, G., Amorim, C.C., 2024. Assessing the Impact of Environmental Conditions on Reflectance Values in Inland Waters Using Multispectral UAS Imagery. Limnol. Rev. 24, 466–490. https://doi.org/10.3390/limnolrev24040027

Souza, A.P., Oliveira, B.A., Andrade, M.L., Starling, M.C.V.M., Pereira, A.H., Maillard, P., Nogueira, K., dos Santos, J.A., Amorim, C.C., 2023. Integrating remote sensing and machine learning to detect turbidity anomalies in hydroelectric reservoirs. Sci. Total Environ. 902, 165964. https://doi.org/10.1016/j.scitotenv.2023.165964

Xiao, Y., Chen, J., Xu, Y., Guo, S., Nie, X., Guo, Y., Li, X., Hao, F., Fu, Y.H., 2023. Monitoring of chlorophyll-a and suspended sediment concentrations in optically complex inland rivers using multisource remote sensing measurements. Ecol. Indic. 155, 111041. https://doi.org/10.1016/j.ecolind.2023.111041