EGU26-14855, updated on 18 Nov 2026
https://doi.org/10.5194/egusphere-egu26-14855
EGU General Assembly 2026
© Author(s) 2026. This work is distributed under
the Creative Commons Attribution 4.0 License.

Benchmarking UAV multispectral sensors and machine learning for water quality estimation

Caio Mello[1,2], Daniel Salim[1,2], Bernardo Souza[1,2], Gabriel Pereira[1], and Camila Amorim[1]
[1]Intelligent Systems for Environmental Monitoring (SIMOA), Department of Sanitary and Environmental Engineering, Federal University of Minas Gerais, Brazil (caiocsmello@gmail.com)
[2]Postgraduate Program in Sanitation, Environment and Water Resources, School of Engineering, Federal University of Minas Gerais, Belo Horizonte, MG, Brazil

The sustainable management of water resources in anthropogenic contexts requires a holistic transition from mere monitoring to comprehensive assessments of water habitats. Urban reservoirs are particularly vulnerable ecosystems, where pressures such as agricultural runoff and untreated sewage discharge drive eutrophication, compromising water quality. Traditional monitoring methods often lack the spatiotemporal resolution required to capture the complex dynamics of these environments. To address this gap, this study evaluates the efficacy of close-range remote sensing combined with Machine Learning (ML) and Explainable Artificial Intelligence (XAI) for estimating optically active water quality parameters (turbidity, chlorophyll-a, and phycocyanin). The research was conducted at the Ibirité Reservoir (Minas Gerais, Brazil), a highly eutrophic urban system serving as a petrochemical industry water supply. Ten monthly field campaigns (August 2024 to May 2025) were conducted, covering both dry and wet seasons, to capture seasonal variability. Data acquisition employed Unmanned Aerial Vehicles (UAVs) equipped with two distinct multispectral sensors: the DJI Phantom 4 Multispectral (P4M – 5 bands) and the MicaSense RedEdge Dual-P (MSR – 10 bands). This setup allowed for a comparative analysis of spectral resolution impacts on model performance. The methodology tested three ML algorithms: Random Forest, CatBoost, and XGBoost. To ensure physical consistency, SHAP (SHapley Additive exPlanations) values were used to interpret the models. This ML-XAI approach assessed: (1) the comparative performance of each sensor and algorithm; and (2) the robustness of the models by identifying the most influential spectral bands for each parameter. Results indicate that ensemble learning algorithms, specifically Random Forest and CatBoost, consistently outperformed others across datasets. The MSR sensor achieved the highest overall accuracy, particularly for Phycocyanin estimation using Random Forest (R^2 = 0.93), compared to the P4M's best result for the same parameter (R^2 = 0.90). Explainable AI analysis revealed the physical drivers behind this performance: for Phycocyanin, the MicaSense models relied heavily on the specific 717 nm and 705 nm (RedEdge) bands. This explains the superior performance, as these narrow bands better resolve the specific spectral features of cyanobacteria compared to the single RedEdge band available on the DJI sensor. Conversely, for Chlorophyll-a, the NIR (842 nm) and Red (650 nm) bands were the dominant predictors. Since both sensors possess these bands, the performance gap was narrower (R^2 = 0.79 for MSR vs. 0.77 for P4M), validating the cost-effectiveness of the

5-band sensor for general pigment monitoring. However, for Turbidity, the additional spectral resolution of the MSR (specifically the 717 nm band) proved decisive, raising accuracy to $R^2 = 0.84$ compared to 0.78 for the P4M. Findings demonstrate that integrating high-resolution multispectral sensing with interpretable ensemble learning offers a scalable and physically consistent tool for monitoring water habitat health, supporting data-driven decision-making in complex urban environments.