
Assessment of Turbidity and Chlorophyll-a Variations in Lagos Lagoon Using Multispectral Remote Sensing

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Abstract

Turbidity and chlorophyll-a are important indicators of aquatic environmental conditions because they provide information about suspended particles, phytoplankton abundance, and changes in water quality. Lagos Lagoon, located in southwestern Nigeria, is exposed to multiple environmental pressures associated with urban development, wastewater discharge, surface runoff, sediment transport, and changing hydrological conditions. Conventional water quality monitoring provides essential measurements but may not adequately capture the spatial and temporal variability of these parameters across extensive aquatic environments. Multispectral remote sensing offers an effective complementary approach by enabling repeated observations of water surface reflectance and the identification of spatial patterns associated with turbidity and chlorophyll-a concentrations. This research examines the application of Sentinel-2A and Landsat-8 imagery, combined with artificial intelligence and machine learning for advanced data analytics, to assess variations in these water quality indicators across Lagos Lagoon. The proposed methodology incorporates satellite image preprocessing, atmospheric correction, water masking, spectral index extraction, machine learning regression, temporal analysis, and validation using in situ measurements. Random Forest, Support Vector Regression, and Gradient Boosting are considered for estimating turbidity and chlorophyll-a from multispectral observations. An experimental framework is developed to compare sensor-specific and integrated models using statistical performance metrics, including the coefficient of determination, root mean square error, and mean absolute error. Since processed satellite imagery and field measurements are not provided for this study, the numerical experimental results are presented as hypothetical examples rather than verified observations. The research provides a reproducible framework for investigating seasonal variability, identifying potential areas of elevated turbidity or chlorophyll-a, and improving the integration of satellite remote sensing with environmental monitoring. The proposed approach can support future research, aquatic ecosystem assessment, and evidence-based water resource management in Lagos Lagoon.

Keywords: Lagos Lagoon, Turbidity, Chlorophyll-a, Multispectral Remote Sensing, Sentinel-2A, Landsat-8, Artificial Intelligence, Machine Learning, Water Quality Assessment, Spatiotemporal Analysis, Advanced Data Analytics.

I. Introduction

Water quality monitoring is an essential component of environmental management because aquatic ecosystems support biodiversity, fisheries, transportation, recreation, and human livelihoods. Turbidity and chlorophyll-a are particularly important indicators because they provide complementary information about suspended particles and phytoplankton biomass. Turbidity describes the cloudiness of water resulting from the scattering of light by suspended materials, including sediment, organic particles, and microorganisms. Chlorophyll-a is a photosynthetic pigment found in phytoplankton and is widely used to estimate algal biomass and assess biological productivity. Changes in these parameters can indicate shifts in runoff, sediment transport, nutrient availability, and aquatic ecological conditions[1]. Their simultaneous assessment is therefore valuable for understanding environmental changes in coastal lagoons.

Lagos Lagoon is an important aquatic ecosystem in southwestern Nigeria, where extensive urban development and economic activities interact with natural hydrological processes. Wastewater discharge, stormwater runoff, shoreline development, industrial activities, and sediment inputs may influence water clarity and phytoplankton growth. These influences can vary substantially between different parts of the lagoon and across wet and dry seasons. Areas receiving substantial sediment inputs may experience elevated turbidity, while areas receiving nutrient-rich wastewater may experience changes in chlorophyll-a concentrations. However, the relationship between these parameters is complex because high turbidity can limit light penetration and suppress phytoplankton growth, whereas moderate nutrient enrichment under suitable light conditions may increase biological productivity. Traditional water quality monitoring relies on field sampling and laboratory measurements. These methods provide important quantitative information but may not capture the full spatial variability of a large lagoon when sampling locations are limited. Satellite remote sensing complements field monitoring by recording reflected sunlight across multiple spectral bands, enabling researchers to identify spatial patterns and revisit the same region over time. Sentinel-2A and Landsat-8 are particularly useful for this purpose because their multispectral sensors provide observations across visible, near-infrared, and shortwave-infrared wavelengths. Their combined application can support the assessment of turbidity and chlorophyll-a, provided that differences in spatial resolution, spectral response, atmospheric correction, and acquisition dates are considered.

This research investigates the assessment of turbidity and chlorophyll-a variations in Lagos Lagoon using multispectral remote sensing and artificial intelligence for advanced data analytics. The study proposes a framework that integrates Sentinel-2A and Landsat-8 observations with machine learning regression, spatial analysis, and field-based validation[2]. It aims to evaluate the relationships between spectral reflectance and water quality indicators, compare alternative predictive models, investigate seasonal variations, and identify locations requiring further environmental investigation[3]. The central objective is to establish a scientifically reproducible approach for monitoring lagoon water quality. The proposed methodology and illustrative experimental results are intended to guide future empirical research and should not be interpreted as confirmed measurements of current conditions in Lagos Lagoon.

II. Study area and environmental characteristics

Lagos Lagoon forms part of the coastal lagoon system of southwestern Nigeria and is influenced by interactions among freshwater inflows, rainfall, tidal circulation, and exchanges with connected waterways. These processes affect the distribution of suspended sediment, nutrients, dissolved organic matter, and phytoplankton. Water movement and residence time can produce substantial differences in the physical and biological properties of different lagoon sections. Consequently, water quality conditions at one sampling location may not represent the conditions elsewhere. Spatially detailed monitoring is therefore necessary to understand the distribution of turbidity and chlorophyll-a across the lagoon.

Urban expansion surrounding Lagos Lagoon creates environmental pressures that may alter the optical characteristics of the water. Surface runoff can transport soil particles, construction materials, and organic debris into drainage channels and connected waterways. Domestic wastewater and industrial discharges may introduce nutrients and other substances that affect aquatic chemistry and biological productivity. Sediment resuspension caused by water movement, human activities, and changing hydrological conditions may also increase turbidity independently of external pollution. The relative contribution of these processes varies spatially, and their effects must be evaluated through field measurements and supporting environmental information.

Seasonal rainfall can influence both turbidity and chlorophyll-a through several interacting mechanisms. During wetter periods, runoff may increase the transport of suspended particles into the lagoon, producing localized increases in turbidity. At the same time, runoff may introduce nutrients that influence phytoplankton growth. However, higher suspended sediment concentrations can reduce light penetration and limit photosynthesis, while increased water exchange can dilute or redistribute nutrients and phytoplankton. During drier periods, reduced runoff may lower some sediment inputs, although localized discharge and biological processes can continue to influence water quality. These contrasting mechanisms make seasonal monitoring essential for interpreting observed changes.

The lagoon's optical complexity creates important challenges for satellite-based assessment. Suspended sediment, chlorophyll-a, colored dissolved organic matter, shallow-water bottom reflectance, and floating vegetation may all influence the measured spectral signal. Atmospheric aerosols, cloud shadows, sun glint, and reflectance from adjacent land can introduce additional errors. Therefore, high reflectance in a particular band cannot automatically be interpreted as evidence of high turbidity or chlorophyll-a without considering the relevant optical conditions. A robust study must distinguish genuine water quality variation from sensor artifacts and environmental influences unrelated to the target parameter.

III. Theoretical foundations of turbidity and chlorophyll-a assessment

Turbidity is an optical property associated with the scattering of light by suspended particles in water. The magnitude of turbidity depends on particle concentration, particle size, shape, composition, and the optical properties of the surrounding water. Fine mineral particles, organic

debris, and plankton may produce different scattering patterns even when their concentrations are similar. Laboratory turbidity measurements are commonly expressed in nephelometric turbidity units, although the exact method and instrument influence the reported values. Satellite-based estimation relies on relationships between water-leaving reflectance and suspended materials, meaning that a locally calibrated algorithm is generally preferable to an unvalidated universal equation.

Chlorophyll-a provides an indication of phytoplankton biomass because the pigment absorbs light strongly in particular spectral regions and influences the reflectance of productive waters. Its concentration is commonly measured in micrograms per liter using laboratory extraction and fluorometric or spectrophotometric techniques. Satellite retrieval methods exploit the relationship between pigment absorption, particle scattering, and reflectance in selected visible and near-infrared bands[4]. In productive and turbid waters, algorithms may use red and near-infrared relationships or combinations of several spectral bands. However, chlorophyll-a estimation is challenging when suspended sediment and dissolved organic matter produce optical signals similar to those associated with phytoplankton.

Turbidity and chlorophyll-a can interact in ways that complicate remote sensing interpretation. High turbidity may arise from mineral sediment without a corresponding increase in phytoplankton biomass. Conversely, increased chlorophyll-a may contribute to elevated particle concentrations while producing distinctive absorption and reflectance characteristics. Nutrient enrichment can stimulate phytoplankton growth, but the resulting response depends on light availability, temperature, water circulation, and biological interactions. Therefore, a strong statistical relationship between turbidity and chlorophyll-a in one period may not remain consistent across different seasons or lagoon locations. Joint assessment should consequently model the two parameters separately while examining their relationship through independent statistical analysis.

Multispectral remote sensing provides a means of investigating these optical relationships across large spatial areas. Each satellite band records reflected energy over a defined wavelength interval, and combinations of bands can be used to characterize the spectral behavior of water. Empirical regression models estimate water quality from relationships between reflectance features and measured concentrations, while machine learning methods can represent more complex nonlinear relationships[5]. The theoretical basis of the proposed research is that a combination of appropriately corrected spectral information, field observations, and statistical learning can improve the estimation of turbidity and chlorophyll-a. The reliability of this approach depends on whether the calibration data represent the actual optical conditions encountered throughout Lagos Lagoon.

IV. Multispectral satellite data and preprocessing

Sentinel-2A provides observations from the Multispectral Instrument, which includes visible, red-edge, near-infrared, and shortwave-infrared bands. Its blue, green, red, and broad near-infrared bands have spatial resolutions of 10 m, while several additional bands are provided at 20 m

resolution. These characteristics make Sentinel-2A useful for investigating spatial variability within coastal waters and identifying relatively localized features. The red-edge bands may contribute to the analysis of productive waters, while visible and near-infrared measurements can support selected turbidity and chlorophyll-a retrieval approaches. Nevertheless, the suitability of a particular band combination must be established for the optical conditions of the study area.

Landsat-8 provides multispectral observations through the Operational Land Imager, including coastal aerosol, blue, green, red, near-infrared, and shortwave-infrared bands. Its multispectral bands generally have a spatial resolution of 30 m, providing useful observations for broader environmental assessment and historical analysis. Landsat-8 can complement Sentinel-2A by increasing the number of available observations and extending the temporal context of the investigation. However, the two sensors do not measure exactly identical spectral intervals, and their different pixel sizes can affect the reflectance values recorded over mixed shoreline and water pixels. Directly combining their observations without accounting for these differences may introduce systematic errors.

The preprocessing workflow begins with selecting cloud-free or minimally contaminated scenes covering the lagoon across different seasons. Surface reflectance products should be evaluated for suitability in aquatic applications, and specialized atmospheric correction methods should be considered because water-leaving reflectance is often much smaller than atmospheric contributions. Cloud masking, cloud-shadow removal, sunglint assessment, geometric alignment, and water-body delineation are essential steps. Pixels affected by shoreline adjacency, floating vegetation, or shallow-water bottom reflectance should be identified where possible. The objective is to create a consistent dataset in which the remaining spectral variations are more likely to represent actual water characteristics rather than atmospheric or geometric artifacts.

The final preprocessing stage harmonizes the spatial and spectral information from the two sensors. Corresponding bands may require bandpass adjustment, and observations should be compared using matched or near-simultaneous acquisition dates when possible. A common spatial grid can support model comparison, but resampling Landsat-8 to a 10 m grid does not increase its original spatial information. The dataset should preserve sensor identity, acquisition date, atmospheric correction method, and quality flags for every observation. These records enable the researchers to distinguish differences arising from actual environmental changes from differences caused by sensor characteristics and processing procedures.

V. Artificial intelligence and machine learning for advanced data analytics

Machine learning offers opportunities to estimate turbidity and chlorophyll-a from complex combinations of multispectral reflectance features. Traditional regression models often rely on individual bands or simple band ratios, while machine learning algorithms can identify nonlinear relationships and interactions among multiple inputs. Random Forest regression is useful because it can accommodate nonlinear behavior, reduce sensitivity to individual observations, and provide feature importance estimates. Support Vector Regression can model nonlinear relationships through kernel functions, while Gradient Boosting algorithms can progressively improve

predictions by learning from previous model errors. These models provide complementary approaches for investigating the relationship between satellite measurements and field-derived water quality indicators.

The proposed analytical framework develops separate predictive models for turbidity and chlorophyll-a. Input variables may include blue, green, red, red-edge, near-infrared, and shortwave-infrared reflectance, together with carefully selected spectral indices. Additional information, such as acquisition season and sensor identity, may be included when it is available at prediction time and scientifically justified. Turbidity models should emphasize spectral features that respond to suspended-particle scattering, while chlorophyll-a models should evaluate pigment-sensitive band relationships and their interaction with other optical constituents. Separate calibration is necessary because the two indicators have different physical meanings and may respond differently to the same spectral changes.

Model training requires field measurements collected at locations and times that correspond closely to the satellite observations[6]. Laboratory turbidity measurements and chlorophyll-a analyses should be linked to the reflectance features extracted from the matching water pixels. The dataset should be divided into training, validation, and independent testing subsets, preferably using spatially and temporally separated observations to reduce data leakage. Hyperparameters should be selected using the training and validation data, while the independent test set should be reserved for final evaluation. This procedure helps establish whether the model generalizes to previously unseen locations and dates rather than merely reproducing patterns in its training data.

Advanced data analytics can extend beyond concentration estimation to include spatial clustering, anomaly detection, and temporal trend analysis. Spatial models can identify groups of locations with similar predicted water quality characteristics, while time-series methods can evaluate seasonal cycles and persistent deviations from typical conditions. Explainable machine learning can indicate which spectral variables contribute most strongly to model predictions and help identify potential problems with the calibration process. However, feature importance does not prove a causal relationship between a band and a pollutant. Model outputs should therefore be interpreted alongside field measurements, hydrological observations, and uncertainty estimates to ensure that statistical associations are not mistaken for confirmed environmental mechanisms.

VI. Experimental design and statistical evaluation

The proposed experiment compares three analytical configurations: a Sentinel-2A-only model, a Landsat-8-only model, and an integrated multisensor model[7]. The experiment is designed to determine whether combining spectral information from both platforms improves the estimation of turbidity and chlorophyll-a. Each configuration should use comparable training and testing conditions, with separate models developed for the two water quality parameters. The field dataset should include a sufficient range of measured concentrations and represent different lagoon locations and seasonal conditions. Where the number of field observations is limited, the resulting estimates should be considered exploratory, and uncertainty should be explicitly reported.

The primary performance metrics include the coefficient of determination, root mean square error, and mean absolute error. The coefficient of determination, or R^2 , measures how well predicted values explain the variability in observed concentrations under the chosen evaluation framework. Root mean square error gives greater weight to large prediction errors, while mean absolute error measures the average magnitude of the absolute differences between predictions and measurements. Bias should also be calculated to determine whether a model systematically overestimates or underestimates the target variable. These metrics should be reported separately for turbidity and chlorophyll-a because their measurement units and concentration ranges differ.

The experimental procedure also evaluates the relationship between satellite reflectance and field observations through correlation analysis and regression diagnostics. Scatterplots of measured versus predicted concentrations can reveal systematic deviations, while residual plots can indicate whether prediction errors vary with concentration or season. Spatially independent testing can help identify whether models calibrated in one part of the lagoon transfer successfully to another[8]. Seasonal validation can similarly determine whether relationships established during dry conditions remain appropriate during wet conditions. These evaluations are important because a model with good overall performance may still produce substantial errors in particular locations or environmental conditions.

Finally, uncertainty analysis should accompany the generation of spatial prediction maps. Bootstrap resampling, repeated model fitting, or other suitable statistical methods can be used to quantify variability in estimated performance[9]. Comparisons between the three model configurations should use matched test observations wherever possible, allowing researchers to assess whether the integrated model provides a consistent improvement. The final analysis should document the satellite scenes, field sampling design, preprocessing settings, model parameters, and evaluation procedures. This documentation is necessary for reproducibility and for distinguishing genuine predictive improvements from differences in data availability or sampling conditions.

VII. Conclusion

The assessment of turbidity and chlorophyll-a variations in Lagos Lagoon using multispectral remote sensing provides a valuable framework for investigating aquatic environmental conditions across space and time. Sentinel-2A and Landsat-8 offer complementary spectral observations that can support water quality estimation when atmospheric correction, water masking, sensor harmonization, and field-based calibration are properly implemented. Artificial intelligence and machine learning can strengthen this process by modeling nonlinear relationships between satellite reflectance and measured water quality indicators, while spatial and temporal analysis can help identify persistent patterns and locations requiring further investigation. The illustrative experimental results demonstrate how an integrated model could potentially improve turbidity and chlorophyll-a estimation compared with individual sensor models, but these values are hypothetical and do not constitute verified findings for Lagos Lagoon. Reliable conclusions about actual water quality conditions require processed satellite imagery, representative laboratory measurements, independent model validation, and explicit uncertainty assessment. By integrating

multispectral observations with environmental measurements and advanced data analytics, future studies can develop more consistent monitoring systems, improve the identification of potential environmental changes, and support evidence-based decisions for the protection and sustainable management of Lagos Lagoon.

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