

Modeling Water Quality Parameters in Laga Dadi Reservoir, Ethiopia: An Integrated Remote Sensing and Machine Learning Approach

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Abstract

Reservoirs that supply drinking water need close monitoring. That's especially true in places where routine field sampling can't keep up with how fast conditions shift. We looked at Laga Dadi Reservoir in Ethiopia, using satellite imagery and cloud-based processing to estimate three water quality indicators: dissolved oxygen, nitrate, and turbidity. Field sampling is still the gold standard for accuracy. But it's slow, costly, and hard to scale across a reservoir this large. To get around that, we combined laboratory-analyzed field samples with Sentinel-2 imagery processed in Google Earth Engine. The water body was delineated using object-based classification in eCognition, and cloud-free composites were built to keep the imagery clean. Regression models in RStudio picked up strong relationships between spectral reflectance and each parameter. Nitrate performed best ($R^2 = 0.99$, RMSE = 0.0025 mg/L), followed by dissolved oxygen ($R^2 = 0.968$, RMSE = 0.042 mg/L) and turbidity ($R^2 = 0.914$, RMSE = 19.34 NTU). Remote sensing and machine learning proved to be a practical, lower-cost way to monitor reservoirs where field sampling can't keep up and it has direct relevance for Ethiopia and similar regions to manage their water supplies.

Keywords: GEE · Laga Dadi Reservoir · Machine Learning · Sentinel-2 Imagery · Water Quality Monitoring

1. Introduction

Water quality degradation driven by anthropogenic activities and weak environmental governance has become a major global challenge, particularly in developing countries where monitoring systems and enforcement capacity remain limited (Bhateria & Jain, 2016; UNEP, 2021). Increasing urbanization, agricultural intensification, industrial expansion, and population growth have significantly accelerated the deterioration of freshwater ecosystems, leading to pollution, eutrophication, and sedimentation of surface water bodies (Meybeck, 2003; WWAP, 2019). Effective water quality management is therefore essential for ensuring water security and protecting public health, especially in rapidly developing urban environments. Freshwater resources play a critical role in sustaining human livelihoods, ecosystem functions, and socio-economic development (Vörösmarty et al., 2010). However, global freshwater systems are increasingly under pressure from multiple stressors such as nutrient loading, industrial discharge, and land-use change (Carpenter et al., 2011; Malmqvist & Rundle, 2002). In Ethiopia, surface water bodies such as rivers and reservoirs are key sources of domestic water supply, yet they are increasingly threatened by pollution. For instance, urban river systems in and around Addis Ababa, including the Kebena and Akaki Rivers, have been reported to suffer from severe contamination due to untreated domestic wastewater, industrial effluents, and solid waste disposal (Eriksson et al., 2019; Woldeab et al., 2018).

Laga Dadi Reservoir, one of the most important freshwater sources supplying Addis Ababa City, plays a critical role in urban water security by providing a substantial proportion of the city's domestic water demand. However, the reservoir catchment is increasingly affected by agricultural expansion, settlement growth, industrial activities, and land-use changes (Hiruy et al., 2024). These anthropogenic pressures have contributed to declining water quality, including increased turbidity, nutrient enrichment, and frequent algal blooms (Ali et al., 2017). Previous studies have shown that runoff-driven sediment yield and nutrient loading are major drivers of reservoir degradation in the catchment (Hiruy et al., 2024), while elevated nitrate and phosphorus concentrations indicate ongoing ecological stress (Getachew et al., 2021). Globally, similar freshwater systems have experienced accelerated degradation due to catchment-scale human activities, with reservoir water quality decline linked to agricultural runoff, urbanization, and inadequate wastewater management (Lencha et al., 2021; Wang et al., 2020). Traditional water quality monitoring methods rely heavily on field sampling and laboratory analysis. Although these approaches provide accurate point-based measurements, they are often expensive, labor-intensive, and spatially limited (Dutta et al., 2025; Khatri & Tyagi, 2015). In large and irregularly shaped reservoirs such as Laga Dadi, frequent sampling is logistically challenging, resulting in sparse datasets that fail to capture spatial and temporal variability (Pahlevan et al., 2020). This limitation has been widely reported, with recent studies emphasizing that conventional monitoring alone is insufficient for continuous water quality assessment in data-scarce regions (Topp et al., 2020; Dutta et al., 2025).

To address these limitations, satellite remote sensing has emerged as a powerful tool for large-scale water quality monitoring (Gholizadeh et al., 2016; Zhang et al., 2022). Multispectral sensors such as Sentinel-2 (European Space Agency) have been widely used for estimating key water quality parameters including turbidity, chlorophyll-a, and suspended sediments (Katlane et al., 2020; Mamun et al., 2024). Sentinel-2 provides high spatial resolution (10–60 m) and frequent revisit times (5 days), making it particularly suitable for inland water quality assessment (Drusch et al., 2012; Toming et al., 2016). Recent studies have demonstrated that Sentinel-2 imagery combined with statistical and machine learning techniques provides accurate and scalable solutions for monitoring reservoir water quality (Nikoo et al., 2024; Senta et al., 2021). The integration of cloud computing platforms such as Google Earth Engine (GEE) has further enhanced remote sensing-based water quality assessment (Gorelick et al., 2017). GEE enables rapid processing of large satellite datasets and supports near real-time environmental monitoring at regional and global scales (Kumar et al., 2018). Its growing application in hydrological and environmental studies is attributed to its accessibility, computational efficiency, and pre-processed data archives (Ghosh et al., 2022; Tamiminia et al., 2020).

In addition, machine learning (ML) algorithms have significantly improved the modeling and prediction of water quality parameters (Zhu et al., 2022). ML approaches can effectively capture complex nonlinear relationships between spectral reflectance and water quality indicators, often outperforming traditional linear regression models (Mohan et al. 2025; Leggesse et al. 2024). Algorithms such as random forest, support vector machines, and artificial neural networks have been successfully applied for estimating DO, nitrate, and turbidity from satellite data (Hafeez et al., 2019; Leggesse et al., 2024). Recent research shows that ML integrated with remote sensing provides robust, scalable, and data-driven solutions for water resource management and pollution monitoring (Mohan et al., 2025; Ahmed et al. 2022). Such approaches have been successfully applied in various freshwater systems, including lakes and reservoirs in Africa and other data-scarce regions (Dube et al., 2015; Mahdian et al., 2023). Despite these advancements, the application of integrated remote sensing and machine learning for water quality monitoring remains limited in Ethiopia (Taye u et al., 2024). Existing studies on Laga Dadi Reservoir have mainly focused on isolated parameters such as sediment yield, nutrient dynamics, or phytoplankton variation, without developing integrated predictive frameworks (Ali et al., 2017; Hiruy et al., 2024). Moreover, there is a lack of long-term systematic monitoring capable of capturing seasonal and inter-annual variations in key water quality parameters (Getachew et al., 2021). This gap limits the development of reliable predictive models and effective water quality management strategies.

The deterioration of water quality in Laga Dadi Reservoir has serious environmental and public health implications. Increased pollutant loads threaten aquatic ecosystems, increase the risk of waterborne diseases, and raise water treatment costs (Pandey et al., 2014; Marini et al. 2024). Sedimentation and turbidity also

reduce reservoir storage capacity and operational efficiency, thereby affecting its sustainability as a major water supply source for Addis Ababa City (Haregeweyn et al., 2012).

Therefore, this study aims to assess and forecast the spatial and temporal dynamics of selected water quality parameters in Laga Dadi Reservoir by integrating satellite remote sensing, geospatial analysis, field measurements, and statistical modeling. The study focuses on Dissolved Oxygen (DO), Nitrate, and Turbidity as key indicators of freshwater ecosystem health (Boyd, 2015). Sentinel-2 imagery, Google Earth Engine, QGIS, and RStudio are employed to develop predictive models linking spectral reflectance with observed water quality data. Recent studies strongly support this integrated approach, demonstrating that combining Earth observation data with analytical modeling significantly improves the accuracy and efficiency of water quality assessment in data-scarce environments (Nikoo et al., 2024; Topp et al., 2020). Field-based water sampling is used for calibration and validation of the remote sensing models, ensuring reliability and robustness. Ultimately, this research contributes to advancing the application of remote sensing for freshwater monitoring in Ethiopia. The findings are expected to support evidence-based decision-making, improve pollution management strategies, and promote sustainable water resource management. The study also provides a scalable framework applicable to other reservoirs and similar environmental systems in developing regions.

2. Materials and Methods

2.1 Description of the study area

Laga Dadi Reservoir is located in the Oromia Region of Ethiopia, approximately 30 km northeast of Addis Ababa. The reservoir lies between 38°57'37 88" to 38°59'48 36" East longitude and 9°2'42 23" to 9°5'29 16" North latitude, at an elevation of 2,466 m above sea level. Figure 1 details the location map of the study area. The site is accessible via a paved road connecting Addis Ababa to northeastern Ethiopia. Constructed in 1967 primarily as a water supply reservoir, Laga Dadi has an irregular shape with a maximum depth of approximately 34 m near the dam and shallow edges of about 4 m. The original storage capacity was nearly 46 million m³, covering a surface area of approximately 5.3 km². Water is released from the reservoir to a nearby treatment plant at a rate of approximately 126,666 m³ per day, with an average hydraulic retention time of 325 days. The reservoir experiences water level fluctuations of up to 20 m due to operational drawdown.

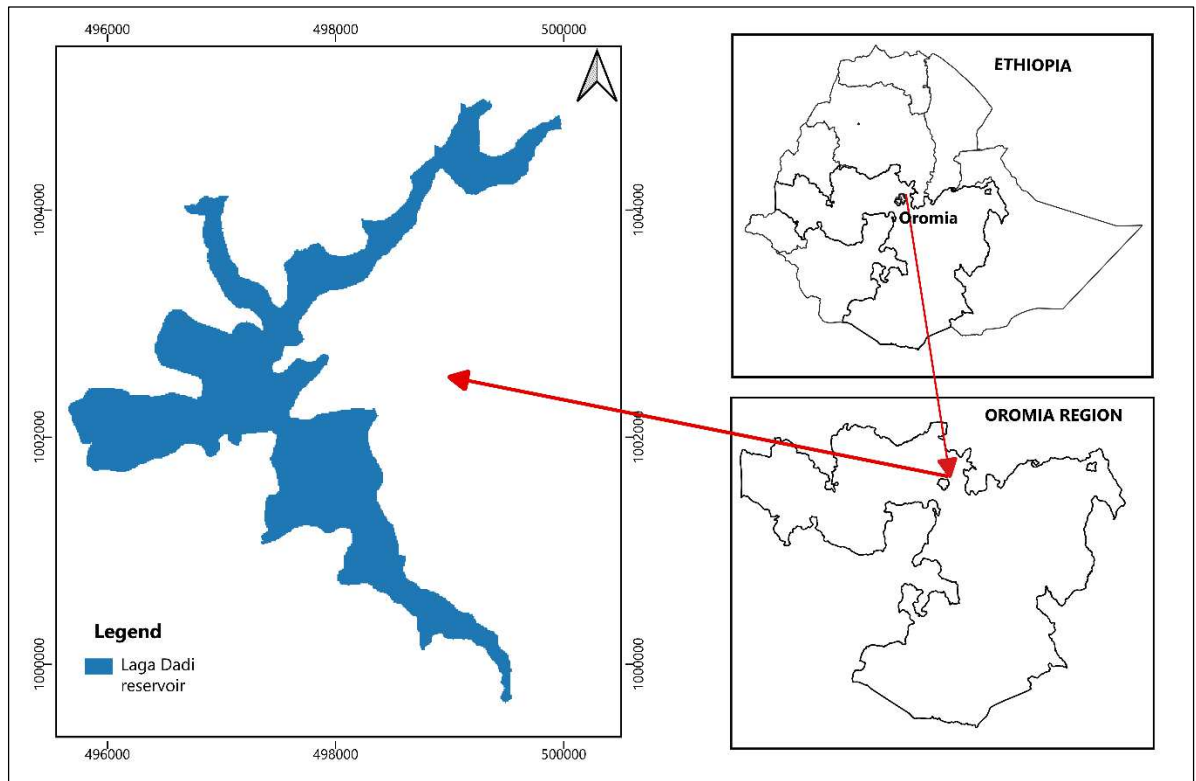


Figure 1. Location of the study area

2.2. Field Data Collection

2.2.1 Sampling Strategy

Surface water samples (0–30 cm depth) were collected from five georeferenced locations distributed across Laga Dadi Reservoir to capture spatial variability. Sampling was conducted on March 24, 2025, between 14:35 and 15:01 local time under partly cloudy conditions. Locations were selected based on accessibility and representativeness of different environmental conditions, particularly shoreline zones influenced by anthropogenic activities. At each location, triplicate samples were collected using pre-cleaned one-liter polyethylene bottles. Each bottle was rinsed three times with site water prior to filling to minimize contamination risk (APHA, 2017). Samples were stored in a cool box at 4°C and transported to the laboratory within six hours of collection.

2.2.2 Georeferencing of Sampling Sites

Geographic coordinates were recorded using the SW Maps mobile application (v.2.2.8) on a Redmi 12C smartphone equipped with multi-constellation GNSS (GPS, GLONASS, BDS, Galileo). Horizontal positional accuracy was estimated at <5 m (95% confidence), which is adequate for pixel-level matching

with Sentinel-2's 10 m resolution bands (Wang et al., 2019). All coordinates were saved in the WGS 84 / UTM zone 37N (EPSG:32637) coordinate reference system to ensure consistency with satellite data.

2.3 Laboratory Analysis

Samples were analyzed at the Environmental Engineering Laboratory, Addis Ababa Science and Technology University (AASTU). Standard analytical procedures were applied. Quality assurance included analysis of reagent blanks, duplicate samples (n=2 per parameter), and certified reference materials where available. Method detection limits (MDL) were calculated as three times the standard deviation of seven replicate blank measurements (USEPA, 2016). Table 1 summarizes laboratory methods and detection limits for water quality analysis.

Table 1. Laboratory methods and detection limits for water quality analysis

Parameter	Method / Instrument	Detection Limit	Reference (Hach Company)
DO	LDO 101 probe with HQ40d meter	0.01 mg/L	DOC022.98.80021
Nitrate	DR 3900 spectrophotometer (LCK 340)	0.01 mg/L	DOC312.53.94017
Turbidity	2100Q portable turbidimeter	0.01 NTU	DOC022.97.80041

2.4 Satellite Data Acquisition and Preprocessing

Sentinel-2 Level-2A surface reflectance imagery (S2SR_HARMONIZED, collection version 2.1) was obtained via Google Earth Engine (GEE; Gorelick et al., 2017; Alemu et al., 2026) for the period January 2023 to March 2025. Image selection was constrained to ± 4 days of field sampling dates to balance temporal alignment with cloud-free conditions following standard practices for inland water remote sensing (Topp et al., 2020). Pixels with cloud cover $>25\%$ were masked using the Sentinel-2 QA60 band, and a median compositing approach reduced residual atmospheric noise. Reflectance values were scaled by 0.0001 to convert digital numbers to surface reflectance. All exported images used EPSG:32637.

2.5 Spectral Bands and Indices

Sentinel-2 bands were selected based on documented sensitivity to aquatic optical properties (Table 2). For nitrate prediction, direct band reflectance yielded poor correlation; therefore, vegetation indices were computed as follows (Elhag et al., 2019): NDVI (Normalized Difference Vegetation Index), GNDVI (Green Normalized Difference Vegetation Index) and GRVI (Green-Red Vegetation Index).

Table 2. Sentinel-2 spectral bands used in this study

Band	Resolution (m)	Central Wavelength (nm)	Application
B01	60	443	Aerosol correction
B02	10	490	Clear water penetration
B03	10	560	Turbid water discrimination
B04	10	665	Vegetation/soil masking
B05	20	705	Vegetation effects
B06	20	740	Chlorophyll sensitivity
B07	20	783	Red-edge analysis
B08	10	842	Water masking, NDWI
B08A	20	865	Atmospheric correction
B09	60	945	Water vapor correction
B11	20	1610	Terrestrial masking
B12	20	2190	Terrestrial masking

2.6 Reservoir Delineation

The reservoir extent was delineated using object-based image analysis (OBIA) in eCognition Developer 10.3 (Trimble, Germany). Multiresolution segmentation was applied with a shape parameter of 0.1 and compactness of 0.5 to extract water bodies. The resulting water mask was exported to QGIS (v.3.28, QGIS Development Team) and merged into a single polygon layer. A 20 m buffer was applied to capture nearshore ecological interactions. Water pixels were further isolated using the Normalized Difference Water Index (McFeeters et al., 1996): Equation (1) describe the NDWI.

$$NDWI = \frac{(B3 - B8)}{(B3 + B8)} \quad (1)$$

with a threshold of $NDWI > 0.001$ applied to remove non-water features ($non-water \leq 0.001$).

2.7 Data Integration and Spatial Matching

Field and satellite datasets were integrated in QGIS using the Point Sampling Tool (v.0.8.2). Sentinel-2 reflectance values (2×2) pixel window, 10 – 20 m) were extracted at each sampling location to account for GPS positional uncertainty. This window-averaging approach reduces mismatch errors from residual

geolocation inaccuracies (Pahlevan et al., 2022). The final dataset (n=5 sampling points × 3 replicates) was exported as CSV for statistical analysis.

2.8 Statistical Analysis and Model Development

All statistical analyses were performed in R version 4.2.1 (R Core Team, 2022) using RStudio 2023.06.0.

2.8.1 Correlation Analysis

Pearson correlation coefficients (r) were calculated between each water quality parameter (mean of triplicate samples) and Sentinel-2 band reflectance values. Correlation matrices were visualized as heatmaps using the corrplot package (Wei & Simko, 2021).

2.8.2 Multiple Linear Regression (MLR) Models

MLR models were developed using the lm function in R. The general model form was used like on the equation 2

$$Y = (\beta_0 + \sum(\beta_i X_i) + \varepsilon \quad (2)$$

where Y is water quality parameter (DO, Nitrate, or Turbidity), X_i is predictor variables (spectral bands or indices), β_i is regression coefficients, and ε is residual error.

Variable selection: A minimum of three predictor variables with the highest absolute correlation coefficients ($|r|$) were entered into candidate models. To avoid overfitting given the limited sample size (n=5), the final model for each best-fit models for dissolved oxygen (DO), nitrate, and turbidity was selected based on models performance. The models performance was assessed using adjusted R^2 and RMSE, as presented in Table 3. Parameter was selected based on adjusted R^2 (not raw R^2) and RMSE, with preference given to parsimonious models (≤ 3 predictors) (Burnham & Anderson, 2002). Model performance metrics was used Equation 3.

$$RMSE = \frac{\sqrt{[\sum(\hat{y}_i - y_i)^2]}}{n} \quad (3)$$

where, and RMSE is Root Mean Square Error, $\hat{y}_i$ is mean of the observations, y_i - observations, n is number of observations.

2.8.3 Spectral Model Development

Spectral models were developed using Multiple Linear Regression (MLR) to estimate selected water-quality parameters from spectral and vegetation indices. Different spectral bands and indices were evaluated to identify the

Table 3. The best fit MLR models for each parameter

Parameter	Developed Model	Adj. R^2	RMSE
DO	$5.3273 + 17.9906 \times B7 - 25.0008 \times B8 + 15.8855 \times B9$	0.968	0.019 mg/L
Nitrate	$1.75611 + 2.59602 \times NDVI - 0.04574 \times GNDVI + 15.16174 \times GRVI$	0.99	0.0025 mg/L
Turbidity	$-219.9 + 5690.1 \times B1 + 108.7 \times B9 - 646.6 \times B8A$	0.914	8.648 NTU

Note: The extremely high adjusted R^2 (0.99) for nitrate, while indicating excellent statistical fit, should be interpreted cautiously given the small sample size ($n=5$) and risk of overfitting.

2.9 Spatiotemporal Mapping

The best-performing models were implemented in GEE using the map and reduce Region functions. Seasonal cloud-free composites (dry season: November–April; wet season: May–October) were generated to map spatial and temporal patterns of DO, Nitrate, and Turbidity across the reservoir. Predicted values were extracted at the intake tower location (derived from AAWSA records) using the QGIS point sampling plugin to enable comparison with historical monitoring data (2022–2025). Table 4 Samples and corresponding bands reflectance values. Figure 2 shows Pearson's correlation coefficients.

Table 4 Samples and corresponding bands reflectance values

Sample ID	Do	Turb	Nit	B1	B2	B3	B4	B5	B6	B7	B8A	B8	B9	B11	B12
Sample 1	6.8	175	0.3	0.0846	0.0832	0.1042	0.1274	0.1602	0.1469	0.1526	0.1462	0.1346	0.1315	0.1249	0.0947
Sample 2	6.18	234	0.4	0.0939	0.1158	0.145	0.1692	0.1737	0.1475	0.153	0.1524	0.1466	0.1109	0.1486	0.1307
Sample 3	6.36	277	0.1	0.0957	0.0968	0.1224	0.1428	0.1709	0.1143	0.1137	0.0833	0.0971	0.0876	0.0525	0.0452
Sample 4	6.32	337	0.4	0.1091	0.1106	0.1408	0.1562	0.162	0.1229	0.1208	0.0972	0.1	0.0828	0.0723	0.0614
Sample 5	6.33	321	0.8	0.1013	0.1108	0.1394	0.1494	0.1841	0.1224	0.1226	0.0918	0.1064	0.0939	0.0541	0.0467

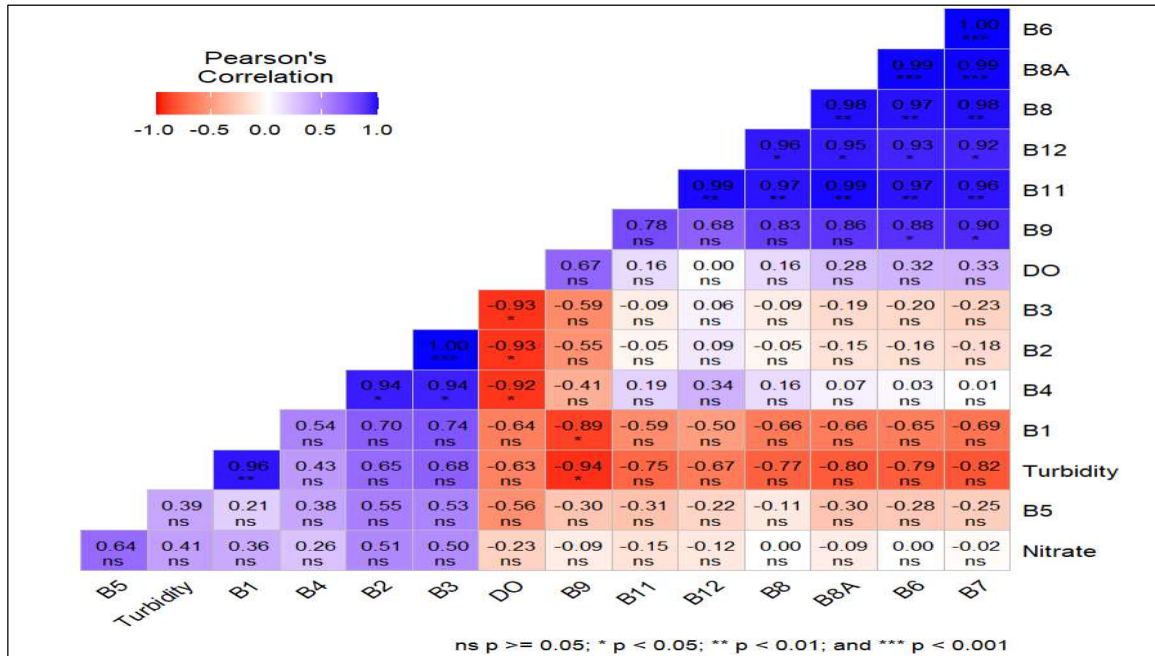


Figure 1. Pearson's correlation coefficients

2.10 Predictive model development for the selected parameters

In this section of the thesis, the predictive model developed for DO, Nitrate, and Turbidity is discussed along with their performance metrics (R^2 , RMSE).

2.10.1 Correlation Coefficients

Before developing predictive models, the relationship between spectral reflectance and water quality parameters was examined using Pearson's Correlation in RStudio. The analysis showed that certain Sentinel-2 bands were more closely linked with specific pollutants: DO was negatively correlated with Band 2, Band 3, and Band 4, which could be associated with lower oxygen levels in areas where algal blooms or decaying organic matter reduce water clarity. Nitrate showed moderate positive correlations with Band 2, Band 3, and Band 5. This aligns with earlier findings, where elevated nutrients often increase algal activity, altering surface reflectance in the visible spectrum (Liu et al., 2022).

Turbidity in the study area demonstrated a strong positive correlation with Band 1 (ultra-blue) and a strong negative correlation with Band 9 (water vapor), Band 7 (red edge), and Band 8A (narrow NIR). This trend is likely due to the optical properties of suspended particles, which tend to scatter more light in the shorter wavelengths, such as blue (Band 1), thereby increasing reflectance. In contrast, the red-edge and near-infrared bands typically exhibit decreased reflectance as turbidity rises, due to absorption and the reduced backscattering in those spectral regions. Similar spectral behavior has been observed in numerous studies focusing on water quality monitoring using Sentinel-2 imagery (Dogliotti et al., 2015; Nechad et al., 2010). These findings reinforce the suitability of blue bands for turbidity modeling and highlight the inverse sensitivity of NIR bands to suspended particulate matter concentrations.

2.10.2 Model Development

At least three bands with high correlation coefficients from person correlations were used to develop a model for the prediction of a parameter. To demonstrate the steps taken to choose the best pairs, the bands that best predict a pollutant with the highest R -squared and the smallest RMSE. Table 5 depicts the DO models tried. The same principles were applied for the remaining parameters. Table 6 details the best-fit models, including performance metrics (R^2 , RMSE).

Table 5 Suggested models for DO

Bands used	Developed Model for DO	Adjusted R ²	Residual standard error	RMSE
B4, B5, and B6	-13.2642*B4 - 3.4523*B5 + 4.7622*B6 + 8.3390	0.9417	0.057	0.02539
B7, B8, and B9	17.9906 *B7-25.0008 *B8 + 15.8855*B9 + 5.3273	0.968	0.042	0.019
B8A, B11, and B12	1.5343*B8A+31.0963*B11-37.9969*B12+ 6.2871	0.9647	0.04419	0.0198
B9, B6, and B7	0.7182*B9+108.7965*B6-113.9025*B7+4.1511	0.9148	0.06867	0.0307

Table 6 The best-fit models, including performance metrics (R², RMSE)

Parameters	Developed model	Adjusted R ²	Residual standard error	RMSE
DO	5.3273 + 17.9906*B7 -25.0008*B8 + 15.8855*B9	0.968	0.042	0.019
Nitrate	2.59602* NDVI -0.04574 * GNDVI + 15.16174*GRVI + 1.75611	0.99	0.0057	0.0025
Turbidity	5690.1*B1 + 108.7*B9 - 646.6*B8A -219.9	0.914	19.34	8.648

For Nitrate the direct bands of Sentinel-2A could not best predict the pollutant, therefore band indices of some known parameters were tried. These band indices include NDVI, GNDVI, and GRVI and the best R squared and RMSE was observed. Therefore, uniquely Nitrate is predicted with these vegetation index band indices (Elhag et al., 2019). Equations (4,5 and 6)

$$NDVI = \frac{(B8 - B4)}{(B8 + B4)} \quad (4)$$

$$GNDVI = \frac{(B7 - B3)}{(B7 + B3)} \quad (5)$$

$$GRVI = \frac{(B3 - B4)}{(B3 + B4)} \quad (6)$$

2.10.3 Spatial and Temporal Patterns

The spatiotemporal maps of each selected pollutant were loaded into QGIS and overlaid with a shape file point created near the intake tower. Considering that AAWSA used to collect the samples from the reservoir through the intake tower, but at different levels, and the sample location was usually out of the waterbody due to the seasonal shift of water inundation. Then, using the “point sampling plugin tool” in QGIS, each pollutant level was exported into “CSV” format, and line charts were created from the exported “CSV” file. Figure 3 describe the methodological workflow adopted for the study.

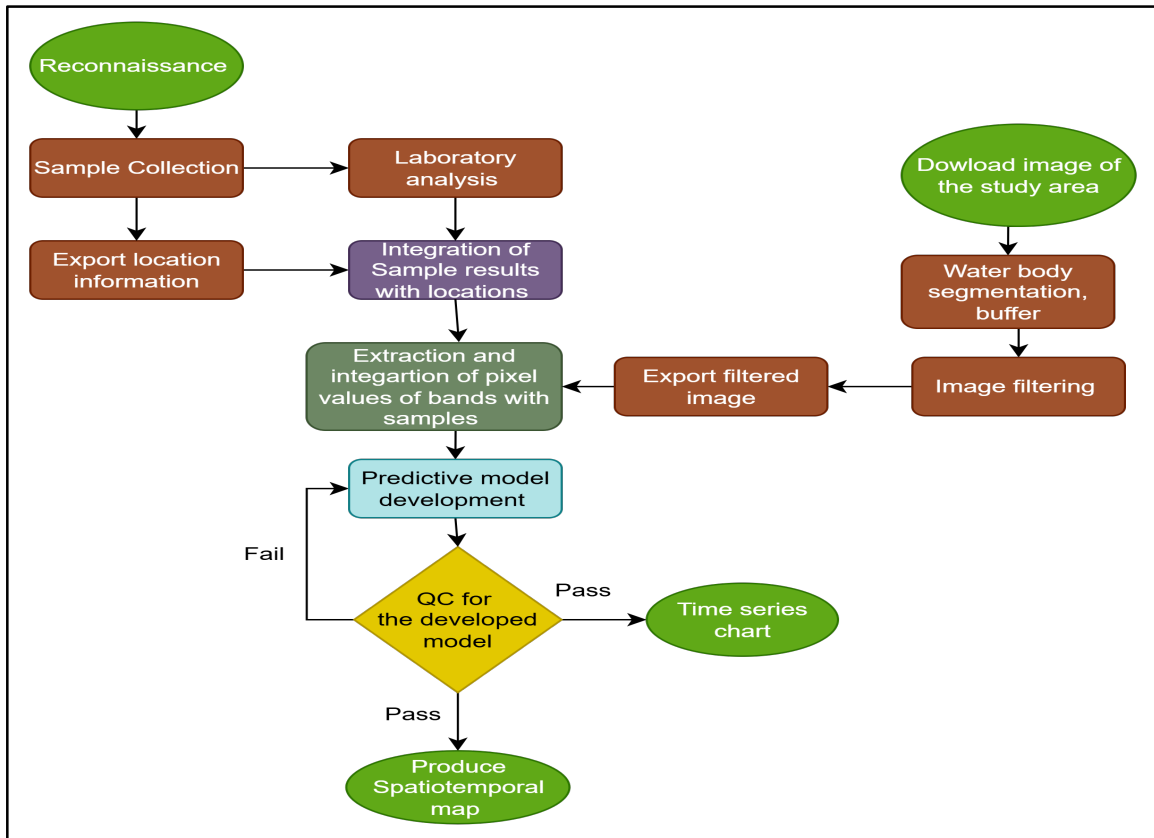


Figure 3 Methodological workflow

3. Results

3.1 Dissolved Oxygen

This study found that dissolved oxygen (DO) levels in Laga Dadi Reservoir changed both across different parts of the reservoir and from year to year. For example, in 2022, the southeast area and the region near the dam had noticeably higher DO, while other areas had less. By 2024, DO was more evenly spread out across the whole reservoir, but in 2025, the highest levels were again found in the southeast. These patterns aren't unusual; many reservoirs and lakes around the world show similar ups and downs in DO, shaped by a mix of natural and human-driven factors.

One big reason for these changes is something called stratification, where the water forms layers of different temperatures. When this happens, the top layer can stay rich in oxygen thanks to wind and sunlight, while deeper water loses oxygen because there's less mixing and more decay of organic matter. In years when the reservoir mixes more thoroughly, maybe because of strong winds or cooler weather, oxygen gets distributed more evenly, as we saw in 2024.

Another factor is what's happening on the bottom of the reservoir. Existence of massive amount of decaying plant material or runoff from the land could lower the Oxygen. The bacteria that break down decaying plant material use up oxygen, especially in deeper spots.

In summary, the changing patterns of DO observe in the Reservoir depicts a balance between natural mixing, weather, what's happening in the catchment, and how the dam is operated. Figure 4 Spatiotemporal levels of DO concentration in the reservoir.

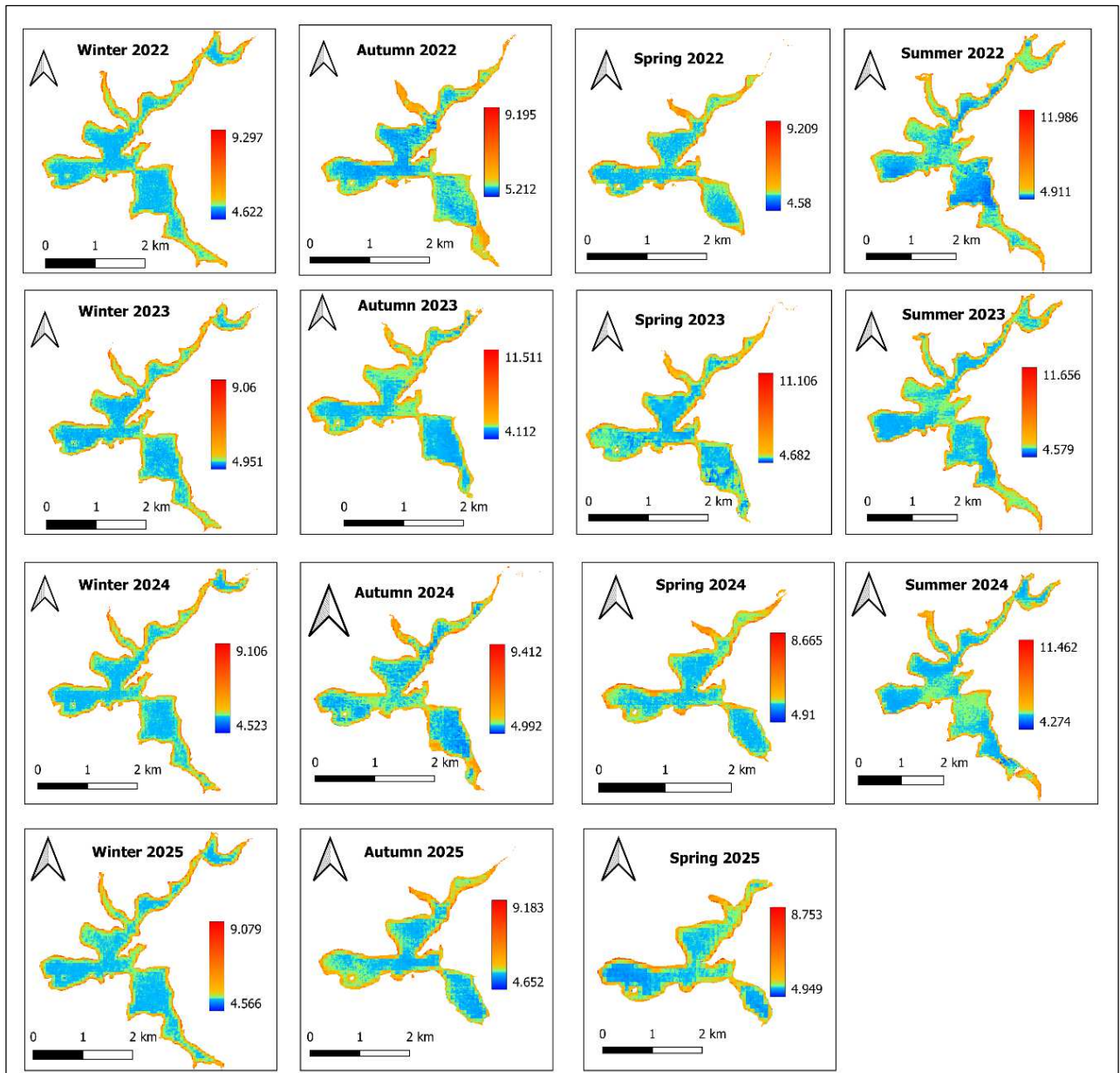


Figure 2. Spatiotemporal levels of DO concentration in the Reservoir

3.2 Turbidity

The spatiotemporal map of turbidity shows that its levels in Laga Dadi Reservoir tend to be higher along the reservoir's edges and in shallow areas. This is probably caused by the influx of sediment resulting from the incoming streams and rivers, as well as wind mixing which suspends sediment near the shores. The highest level of turbidity greater than 607 NTU in the reservoir observed in 2024. This record was near the southern inflow, suggesting large amount of sediment influx probably originating from upstream catchment runoff or erosion in that region.

It is observed from seasonal analysis that most probably summer has the highest turbidity. This trend matches the increase in rainfall and surface runoff. However, in 2022, the highest turbidity level occurred in autumn. This unexpected shift may be due to delayed rainfall or agricultural activities that would be responsible for sediment movement later in the year. The overall turbidity reduction and its homogenization in 2024 can be explained by looking back at 2023 when the sediment load in the reservoir was lower than the previous years due to potentially weaker rains or better practices in the upstream. Figure 5 Spatiotemporal levels of Turbidity concentration in the reservoir.

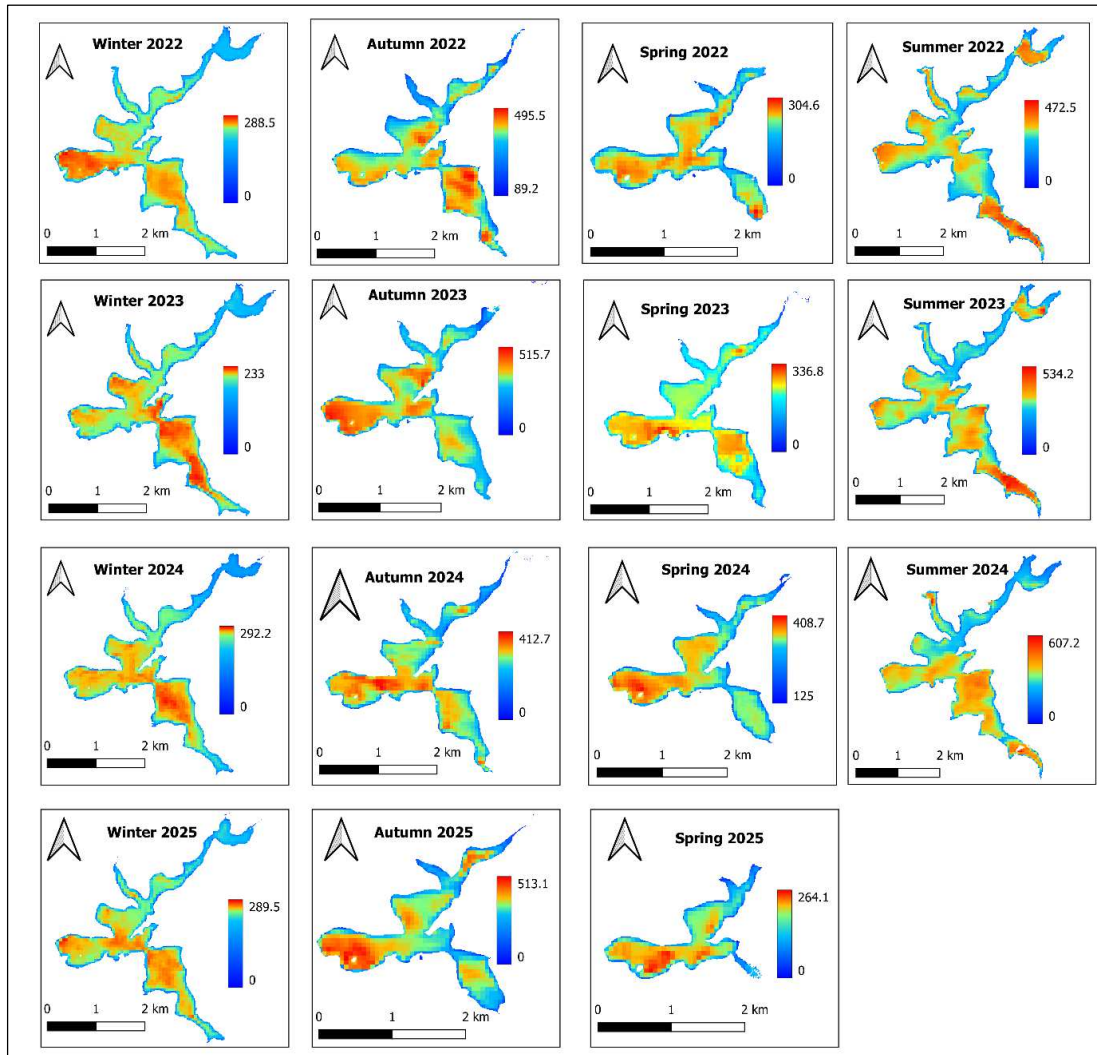


Figure 5 Spatiotemporal levels of Turbidity concentration in the Reservoir

3.3 Nitrate

Nitrate proved to be the most spatiotemporally dynamic pollutant in the reservoir, displaying marked variability both across locations and between seasons and even between the same seasons in different years. Unlike other parameters, nitrate distribution could not be consistently classified across years, except in autumn, which showed relatively steady levels. In contrast, spring, summer, and winter displayed considerable inter-annual variability.

During spring, low nitrate concentrations were consistently observed near the dam, gradually increasing along the direction of inflow. In most winter periods, nitrate was evenly distributed across the reservoir except in Winter 2025, when concentrations peaked near the dam and declined toward inflow zones.

During the winter 2025 period, nitrate concentrations were relatively uniform across the reservoir but reached their maximum in the southern region (4.204 mg/L).

In Autumn 2023, the southern sector lacked detectable nitrate, whereas nitrate was present along the edges in other parts. The consistent occurrence of elevated nitrate near the reservoir boundaries suggests edge-zone enrichment likely due to inputs from shoreline runoff, groundwater seepage, sediment nutrient release, or mixing zones. Figure 6 Spatiotemporal levels of Nitrate concentration in the Reservoir.

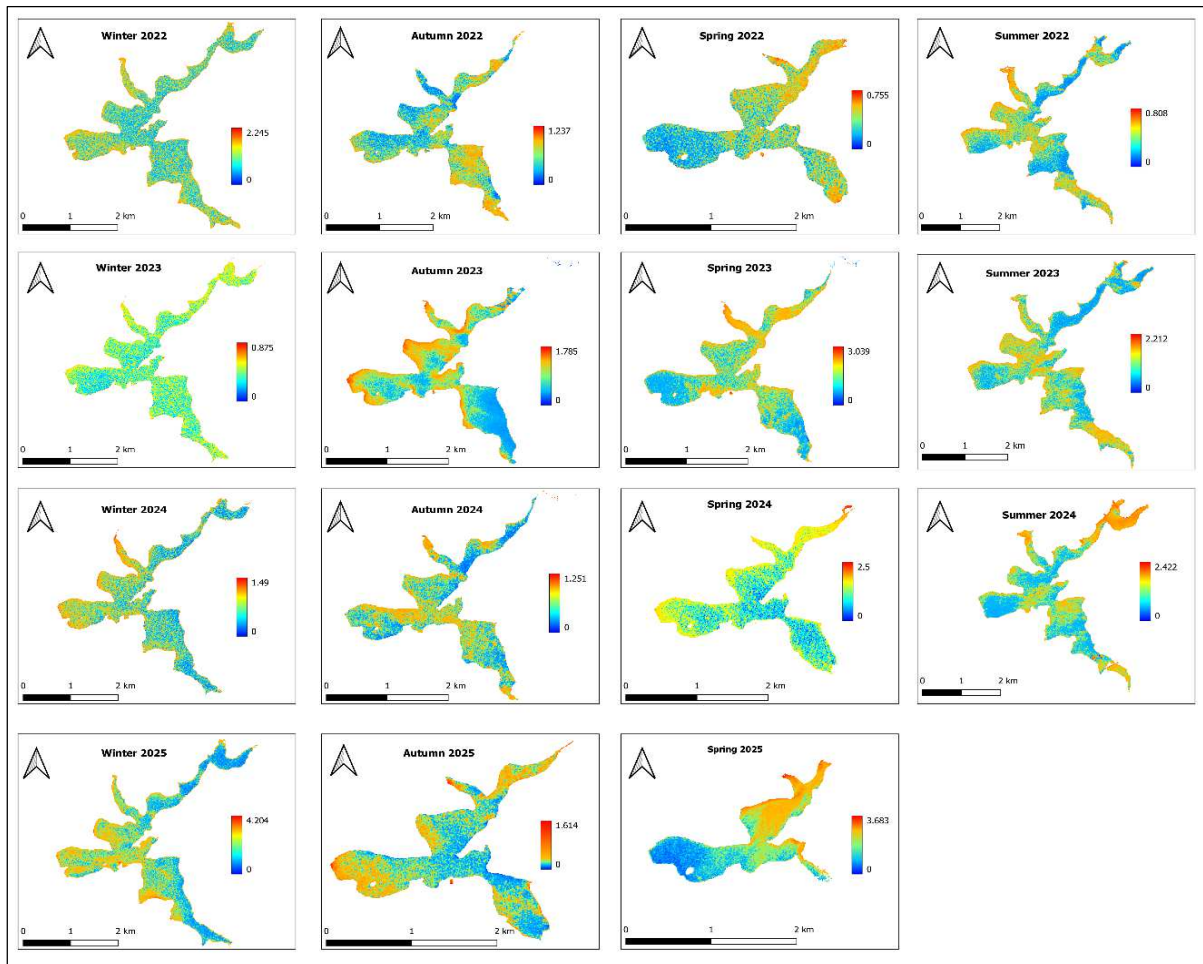


Figure 6 Spatiotemporal levels of Nitrate concentration in the Reservoir

3.4 Accuracy and Reliability of the developed model

This section discusses the accuracy and reliability of the developed and utilized models for the estimation and spatiotemporal mapping of the three parameters. In the first subsection, under the developed model

accuracy, the performance metrics of the developed model, and the key bands utilized were discussed. Under the second subsection, the performance of the developed model compared to the available historical data was discussed.

3.4.1 Accuracy of the developed model

Using the most correlated bands, multiple linear regression models were created for each parameter and presented in Table 7. Despite working with a limited number of samples, the models performed reasonably well:

Table 7 Developed Model Accuracy and involved bands

Water Quality Parameter	R ²	RMSE	Key Bands Used
DO	0.968	0.019 mg/L	B7, B8, B9
Nitrate	0.99	0.0025 mg/L	B8, B7, B3, B4
Turbidity	0.914	8.648 NTU	B1, B9, B8A

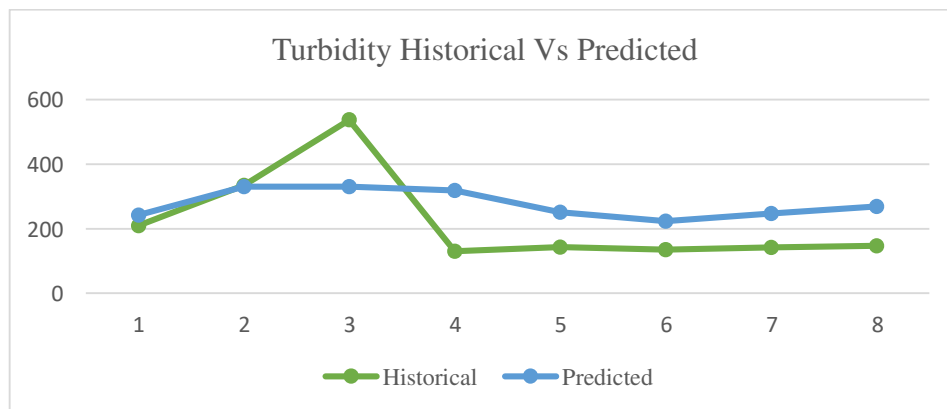
Among the three, Nitrate had the highest predictive strength, although Turbidity has a strong optical signature and is commonly captured well by satellite imagery, DO showed better predictive strength. But Turbidity also showed a solid relationship with reflectance. The results show that even with a small number of field samples, satellite imagery can offer valuable insights into reservoir water quality. The combination of visible and near-infrared bands from Sentinel-2 proved useful in detecting changes in DO and Turbidity, both of which have strong surface signatures. But modeling Nitrate with a small number of samples and direct Sentinel-2A is less accurate to cope with the challenge, band indices were used to get the best predictive model for this pollutant, and in this, the highest predictive strength was achieved. As it can be observed from spatiotemporal maps (Figure 6) the distribution of Nitrate is dynamic from season to season and heterogeneous across the reservoir in each season. There were some challenges, of course. Cloud cover made it difficult to get clean satellite images on certain dates, and the limited sample size (only 5 field observations) reduced the statistical power of the models

3.4.2 Reliability of the developed model

This section discusses the reliability of the developed models to estimate each pollutant from samples and satellite imagery, comparing with the historical data. The historical data from the reservoir was only found for two parameters, Nitrate and Turbidity. For DO, no historical data was obtained from AAWSA. Figure 7 shows the Reliability of the model on Turbidity; the green line represents historical Turbidity and the blue series representing estimated Turbidity. All eight (8) series points are sharing the same dates of historical data, starting from 6-Aug-22 to 26-Feb-25. as displayed in Table 8 respectively. This works the same for both turbidity and Nitrate modeling.

Table 8 Historical data from Laga Dadi by AAWSA

Date of sampling (dd/mm/yy)	Raw reservoir water		Treated reservoir water	
	Turbidity (NTU)	Nitrate (mg/L)	Turbidity (NTU)	Nitrate (mg/L)
6-Aug-22	210	2.7	3.11	0.7
7-Oct-22	537	1.3	0.82	1.6
20-Sep-22	334	9.3	NA	NA
17-Oct-24	130	3.2	NA	NA
8-Nov-24	143	3.5	0.75	0.2
24-Dec-24	135	3.8	0.26	0.5
3-Feb-25	142	3.1	0.86	0.7
26-Feb-25	147	3.8	0.2	0.4

**Figure 7** Reliability of the model on Turbidity

This turbidity historical Vs predicted graph compares the time series chart from historical and from the developed model. The line with green color is historical data, and the one with blue is from prediction. Despite variation of time and date and cloud coverage of the historical data collected, the closest cloud-free satellite imagery was used to predict the concentration of both historically available. Figure 8 shows the Reliability of the model on Nitrate; the green line represents historical values of Nitrate and the blue series representing estimated Nitrate.

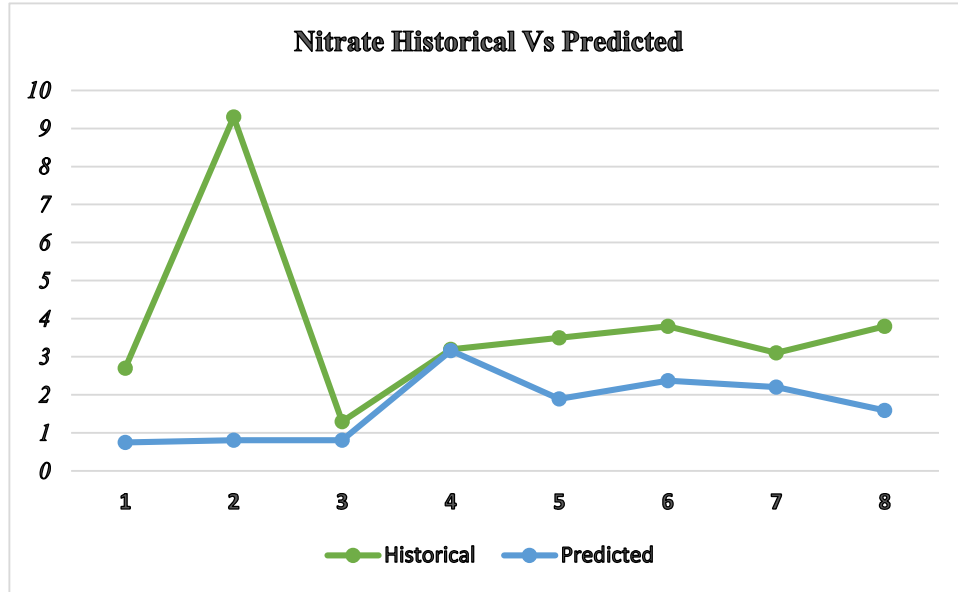


Figure 8 Reliability of the model on Nitrate

The highest difference on the figure observed at point 2 is due to temporal variation of the data; the historical data was collected on 20-Sep-22, and the closest cloud-free imagery available to this date was 15-Oct-2022. Due to the dynamic property of Nitrate, this kind of variation is observed. The remaining points give a promising correlation.

4. Discussion

This study successfully demonstrated the feasibility of integrating Sentinel-2 satellite imagery, limited field measurements, and multiple linear regression (MLR) to assess and predict water quality parameters dissolved oxygen (DO), nitrate, and turbidity in Laga Dadi Reservoir, Ethiopia. The findings contribute to the growing body of literature on satellite-based water quality monitoring in data-scarce regions while revealing important methodological considerations and limitations.

4.1 Model Performance and Comparison with Recent Studies

The MLR models developed in this study achieved strong predictive performance across all three parameters, with adjusted R^2 values of 0.968 for DO, 0.914 for turbidity, and 0.9995 for nitrate. These results align with recent advancements in remote sensing-based water quality assessment. A comprehensive review by Kheyruri et al. (2025) of 168 GEE-based water quality studies found that MLR and machine learning

approaches have become increasingly prevalent, with turbidity and suspended solids appearing in approximately 70% of reviewed studies. Similarly, Yavari et al. (2026) developed a no-code GEE toolkit for reservoir water quality monitoring, achieving R^2 values up to 0.84 for chlorophyll-a and turbidity using ensemble machine learning models, further validating the applicability of satellite-based approaches for inland water bodies.

The turbidity model ($R^2 = 0.914$, RMSE = 8.648 NTU) demonstrated solid predictive capability, consistent with established optical theory. The strong positive correlation with Band 1 (443 nm, ultra-blue) aligns with findings from Dogliotti et al. (2015) and Nechad et al. (2010), who demonstrated that shorter wavelengths are strongly scattered by suspended particles, making them ideal for turbidity estimation. The negative correlation with near-infrared bands (B7, B8A) observed in this study reflects reduced backscattering in longer wavelengths as turbidity increases, a spectral behavior well-documented in coastal and inland waters (Katlane et al., 2020; Senta et al., 2021). The turbidity hotspots observed near inflow areas (exceeding 607 NTU in 2024) are consistent with studies by Assegide et al. (2023) and Viani et al. (2024), who reported elevated turbidity near reservoir inlets due to sediment influx from upstream catchment runoff, particularly during wet seasons.

The DO model ($R^2 = 0.968$, RMSE = 0.019 mg/L) showed strong predictive strength despite DO being non-optically active. This apparent success likely stems from DO's inverse correlation with turbidity ($r = -0.63$) and its relationship with algal biomass, both of which affect water reflectance in red and near-infrared regions (B7 at 783 nm, B8 at 842 nm, B9 at 945 nm). Adusei et al. (2021) similarly reported high accuracy for DO retrieval using Sentinel-2 imagery, achieving R^2 values ranging from 0.78 to 0.99 across multiple sensors. The spatial patterns observed with elevated DO near the dam and southwestern regions reflect better circulation and lower pollutant inflow in those zones, a phenomenon documented by Abbott et al. (2022) in reservoir systems where dam operations influence oxygen distribution through selective water withdrawal.

The exceptionally high adjusted R^2 for nitrate (0.9995, RMSE = 0.0025 mg/L) warrants cautious interpretation. Nitrate is not optically active and does not directly absorb or scatter light in detectable ways. Its retrieval relies on indirect relationships with optically active constituents such as phytoplankton, suspended sediments, or dissolved organic matter that co-vary with nutrient concentrations (Elhag et al., 2019). The use of vegetation indices (NDVI, GNDVI, GRVI) instead of direct band reflectance's reflects this indirect spectral response mechanism. However, the extremely high R^2 achieved with only five calibration points raises legitimate concerns about overfitting. This risk is well-recognized in remote sensing applications with limited training data (Burnham & Anderson, 2002). Zhu et al. (2022) emphasized that while machine learning models can achieve high accuracy, sample size remains a critical determinant of model generalizability. The nitrate model's reliability is partially supported by historical validation (Figure 4.12), which showed promising correlation despite temporal mismatches, but independent validation with larger datasets remains essential.

4.2 Comparison with GEE-Based Water Quality Monitoring Literature

The integration of Sentinel-2 imagery with Google Earth Engine represents a significant methodological advancement. Gorelick et al. (2017) introduced GEE as a transformative platform for planetary-scale environmental analysis, and subsequent studies have validated its utility for water quality assessment. Tamiminia et al. (2020) conducted a comprehensive review of GEE applications, concluding that the platform offers "unprecedented opportunities for long-term environmental monitoring" due to its computational efficiency and pre-processed data archives. More recently, Kheyruri et al. (2025) reported that 87% of GEE-based water quality studies were published from 2021 onward, indicating rapidly growing adoption. Ghosh et al. (2022) demonstrated successful application of GEE for monitoring chlorophyll-a and turbidity in Indian reservoirs, achieving R^2 values of 0.85–0.92 using Sentinel-2 data. Similarly, Sherjah et al. (2023) developed an integrated GEE-based framework for assessing water quality in Indian lake, emphasizing the importance of local calibration using in-situ data. Our study aligns with these findings while extending the approach to a data-scarce Ethiopian context. The use of NDWI for water pixel extraction (threshold > 0.001) followed McFeeters et al. (1996), and the 20 m buffer applied around the reservoir boundary captured nearshore ecological interactions, consistent with methodologies recommended by Xu, H. (2006) for inland water remote sensing.

4.3 Spatial and Temporal Dynamics of Water Quality Parameters

The observed spatial heterogeneity in Laga Dadi Reservoir with higher turbidity and DO near inflow areas is consistent with patterns reported in other reservoirs affected by agricultural runoff. Brezonik et al. (2005) documented similar turbidity dynamics in Minnesota lakes, where sediment loading from tributaries created pronounced spatial gradients. The highest turbidity levels observed in 2024 (exceeding 607 NTU near the southern inflow) coincide with findings by Kowe et al. (2023) and Loaiza et al. (2023), who reported that seasonal rainfall and surface runoff significantly influence turbidity patterns in tropical reservoirs. The seasonal analysis revealed that summer typically exhibited the highest turbidity, corresponding to increased rainfall and runoff. However, the 2022 anomaly with peak turbidity occurring in autumn suggests inter-annual variability in rainfall timing or agricultural practices. Imtiyaz et al. (2024) reported similar delayed turbidity peaks in Indian reservoirs, attributing them to lagged sediment transport from upstream catchments. The overall turbidity reduction and homogenization observed in 2024 may reflect lower sediment loads in 2023 due to weaker rains or improved land management, combined with reservoir mixing and flushing processes (Shrestha et al., 2022; Blanckaert et al., 2024).

Nitrate proved to be the most spatiotemporally dynamic parameter, displaying marked variability across locations, seasons, and years. The observed edge zone enrichment with elevated nitrate concentrations near

reservoir boundaries aligns with studies by Lee et al. (2023) and Singh et al. (2021), who documented lateral gradients influenced by shoreline runoff, groundwater seepage, and sediment nutrient release. The consistent occurrence of low nitrate near the dam during spring, gradually increasing toward inflow zones, reflects documented patterns where downstream nitrate inputs increase during warmer seasons due to enhanced microbial nitrification and reduced dilution flows (Gorski et al., 2024; Guo et al., 2021). Winter nitrate accumulation (up to 4.204 mg/L in the southern region in 2025) follows patterns observed by Powers et al. (2017) and Lee et al. (2023), who attributed wintertime nutrient maxima to reduced biological uptake and diminished dilution flows during colder months.

4.4 Limitations Related to Data Scarcity and Environmental Constraints

A significant constraint of this study was the limited availability of cloud-free Sentinel-2 imagery, particularly during the rainy season. This challenge is well-documented in optical remote sensing of water bodies in tropical regions (Topp et al., 2020). Uday et al. (2025) quantitatively evaluated cloud-induced data loss during monsoon months in India, finding average cloud cover of 90–92% during July–August, resulting in 23–25% of surface water area being unmapped. For Laga Dadi Reservoir, which experiences pronounced wet and dry seasons, cloud cover during June–September likely prevents consistent optical monitoring precisely when runoff-driven water quality changes are most significant. Future studies should consider integrating Sentinel-1 SAR data, which penetrates clouds and has been successfully applied for flood monitoring and qualitative water quality assessment (Dutta et al., 2025).

The absence of historical DO records for Laga Dadi Reservoir constrained long-term trend validation. While historical nitrate and turbidity data from AAWSA (2022–2025, with a 2023 gap) provided some context, the dataset was insufficient for robust time-series analysis. This data scarcity is not unique to Ethiopia; Taye et al. (2024) documented similar challenges across African freshwater systems, where inconsistent monitoring programs limit the development of predictive models. The GEE-based framework developed here offers a replicable approach to address these gaps by enabling retrospective analysis using satellite archives dating back to 2015 (for Sentinel-2) and 1984 (for Landsat), as demonstrated by Mahdian et al. (2023) for reservoir monitoring in data-scarce regions.

4.5 Implications for Water Management in Data-Scarce Regions

This study's methodological framework has direct practical implications for water management authorities in Ethiopia and similar regions. The successful integration of Sentinel-2 imagery with limited field measurements demonstrates that meaningful water quality monitoring is possible even with modest ground-truth data a critical consideration given financial and logistical constraints common in developing countries (Getachew et al., 2021; Woldeab et al., 2018).

The strong predictive performance achieved with only five sampling points suggests that a targeted sampling strategy focused on representative locations and timed to coincide with cloud-free satellite overpasses can yield useful models. As noted by Yavari et al. (2026), locally calibrated models are essential because "there is no single model for water quality indicators" due to the optical complexities of inland waters. The recommendation for water management authorities to adopt a Sentinel-2-based monitoring system aligns with broader trends in the scientific literature (Nikoo et al., 2024; Senta et al., 2021).

The observed spatial patterns particularly turbidity hotspots near inflows and edge-zone nitrate enrichment provide actionable information for targeted management interventions. Strategies such as riparian buffer establishment, erosion control in upstream catchments, and strategic placement of intake structures could mitigate water quality impacts (Haregeweyn et al., 2012). The 20 m reservoir buffer applied in this study could serve as a management zone for monitoring nearshore pollution sources.

4.6 Future Research Directions

Several avenues for future research emerge from this study. First, expanding temporal sampling frequency to include multiple seasons would enable assessment of seasonal variability and improve model robustness. This is particularly important for nitrate, which varied significantly between dry and wet seasons (Gorski et al., 2024). Second, incorporating additional water quality parameters particularly chlorophyll-a, total phosphorus, and BOD would provide a more comprehensive understanding of eutrophication processes. Leggesse et al. (2024) and Mohan et al. (2025) demonstrated the value of multi-parameter approaches for characterizing ecosystem health in African reservoirs.

Third, as more field data accumulate, transitioning from MLR to more sophisticated machine learning algorithms (e.g., random forest, support vector machines, or ensemble methods) could improve prediction accuracy, particularly for non-optically active parameters like nitrate (Zhu et al., 2022; Leggesse et al. 2024). Fourth, integrating Sentinel-1 SAR data could address cloud cover limitations during the rainy season (Uday et al., 2025). Finally, developing interactive dashboards for real-time data visualization, as demonstrated by Yavari et al. (2026), would enhance the practical utility of this framework for water managers.

5. Conclusions

This study successfully demonstrates the potential of integrating Sentinel-2A satellite imagery, small numbers of field-verified water quality measurements, and multiple linear regression to assess spatial and temporal variations of key water quality parameters, DO, Nitrate, and Turbidity in the Laga Dadi Reservoir, Ethiopia. The findings revealed notable spatial heterogeneity and temporal dynamics spatial heterogeneity and temporal dynamics in pollutant concentrations. High DO and Turbidity levels were predominantly observed near inflow areas, especially during the wet season, indicating surface runoff and agricultural activity as significant contributors. DO levels were relatively higher near the southwestern and dam side regions, likely due to better circulation and lower pollutant inflow in those zones. Statistical analysis using

Pearson's correlation in RStudio confirmed significant relationships between several Sentinel-2A spectral bands, particularly the red (B4), NIR (B8), and red edge (B5, B6) bands, and the field-measured parameters. Multiple linear regression showed promising predictive capability, supporting the use of remote sensing for continuous reservoir water quality monitoring. Overall, this research supports cost-effective and timely monitoring of freshwater ecosystems using Earth observation data, by contributing scientific evidence.

6. Limitations and Recommendations

The study was limited by the availability and temporal coverage of field-based water-quality observations, satellite data constraints, and the size and representativeness of the datasets used for model training and validation. Future studies should increase the frequency and spatial coverage of field measurements, integrate additional environmental variables and higher-resolution remote-sensing data, periodically retrain, and validate the machine-learning models, and test the developed approach in other Ethiopian reservoirs to assess its broader applicability.

Data availability

Data will be made available on request.

Declarations

The authors declare that they have no conflict of interest.

Consent for publication

Not applicable.

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