

Assessing Eutrophication in a Small Polluted Reservoir Through Landsat 8 Band-Ratio Models: The Case of Xuan Khanh Reservoir, Hanoi, Vietnam

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ABSTRACT

This study develops an integrated framework for monitoring eutrophication in Xuan Khanh Reservoir (XKR), Hanoi, Vietnam, by combining in-situ observations with Landsat 8 (L8) reflectance data. A total of 66 field measurements collected during four surveys (October 2024-July 2025) were used to calibrate an empirical model for estimating the Trophic State Index (TSI) from L8-derived reflectance. The near-infrared to red ratio (B5/B4) achieved the best performance ($R^2=0.81$; RMSE=2.4). Nineteen cloud-free L8 images acquired between July 2021 and July 2025 were then applied to map spatiotemporal TSI variations. Results show that XKR consistently remained in a highly eutrophic to hypereutrophic state, with TSI values ranging from 64 to 82. Spatial patterns revealed persistent hotspots in shallow northern zones and inlet-connected areas, driven by external nutrient inputs and surrounding land-use pressures. These findings demonstrate the value of L8 as a cost-effective monitoring tool for small, polluted reservoirs, offering evidence to guide nutrient reduction, wastewater management, and land-use regulation. The proposed approach provides transferable insights for long-term trophic state assessment and can support policy decisions aimed at safeguarding freshwater resources in data-limited regions.

HIGHLIGHTS

A Landsat-8-based framework was applied to eutrophication monitoring in a small reservoir. An empirical NIR-to-red band-ratio model was developed to estimate the Trophic State Index (TSI). Four-year spatiotemporal variability revealed persistent eutrophic to hypereutrophic conditions and localized hotspots.

1. INTRODUCTION

Eutrophication remains one of the most consequential stressors on freshwater ecosystems, degrading water quality, ecosystem services, and human health. Small reservoirs, particularly those located in urban and peri-urban environments, are especially susceptible to eutrophication due to their limited water volume, shallow depth, restricted flushing capacity, and disproportionately high nutrient inputs (Dorgham, 2014). These characteristics result in rapid and pronounced fluctuations in algal biomass and water clarity, making eutrophication dynamics in small reservoirs both environmentally critical and

technically challenging to monitor using conventional in-situ approaches. Conventional field-based monitoring programs often suffer from sparse temporal sampling and limited spatial representativeness, which are insufficient to capture the high spatio-temporal variability characteristic of eutrophic small reservoirs. Satellite remote sensing provides a complementary solution by offering synoptic, repeatable observations over extended time periods (Batina and Krtalic, 2024). Among available satellite missions, Landsat-8/OLI (L8) remains particularly valuable due to its free access, global coverage, 30-m spatial resolution, and decade-long

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data continuity, enabling the monitoring of small reservoirs and long-term water-quality change, despite its relatively coarse 16-day revisit frequency (Olmanson et al., 2020).

The Trophic State Index (TSI) is a widely adopted framework for characterizing eutrophication by integrating key water-quality variables into a standardized 0-100 scale. Among its components, chlorophyll-a concentration (Chla) and Secchi disk depth (SDD) are directly linked to the optical properties of surface water and can therefore be reliably estimated from satellite-derived reflectance. Consequently, TSI, particularly TSI (Chla) and TSI (SDD), has been widely applied in remote sensing-based assessments of lake and reservoir trophic status. Numerous studies have demonstrated robust relationships between Landsat-derived reflectance and SDD (Lee et al., 2016; Liu et al., 2020; Song et al., 2022) or Chla (Karimi et al., 2024; Vinh et al., 2019; Yadav et al., 2019), enabling the estimation of TSI across diverse aquatic environments (Hu et al., 2022; Li et al., 2022; Lyu et al., 2022; Vinh et al., 2022).

A growing body of research has confirmed the feasibility of Landsat-8 for monitoring eutrophication through empirical band-ratio models, with reported coefficients of determination (R^2) typically ranging from 0.57 to 0.75 (e.g., Watanabe et al., 2015; Hu et al., 2021; Zhou et al., 2019; Vinh et al., 2022; Kiwanuka et al., 2025a). However, most existing studies have primarily focused on large lakes and reservoirs, where optical conditions are relatively stable and spatial resolution constraints are less pronounced (Hu et al., 2022; Li et al., 2022; Lyu et al., 2022). Consequently, the applicability and robustness of Landsat-based approaches for small, optically complex reservoirs remain insufficiently explored. In such systems, reliable satellite-based monitoring is further challenged by a combination of physical, optical, and anthropogenic factors.

Narrow water bodies are particularly susceptible to atmospheric correction uncertainties and adjacency effects, whereby reflectance signals are contaminated by surrounding land surfaces (Ogilvie et al., 2018). High turbidity, elevated suspended sediment concentrations, and shallow bathymetry further complicate optical conditions, often weakening the relationship between surface reflectance and key water-quality variables such as Chla or SDD (Palmer et al., 2015). Moreover, untreated or partially treated wastewater inputs, characterized by elevated nitrogen and phosphorus loads and increased organic matter,

can intensify algal growth and accelerate eutrophication processes, leading to pronounced spatial heterogeneity and temporal variability (Di Francesco et al., 2022; Owusu et al., 2022). These factors, when combined with frequent cloud cover in tropical regions, pose significant challenges for reliable Landsat-based eutrophication monitoring in small reservoirs (Keith et al., 2018). Despite their heightened ecological vulnerability and socio-economic importance as sources of water supply, aquaculture, and recreation, small eutrophic reservoirs remain underrepresented in remote sensing-based eutrophication studies (Di Francesco et al., 2022; Owusu et al., 2022). This underrepresentation limits the availability of timely and spatially explicit information required to support effective management and mitigation strategies at the local scale.

The distinguishing contribution of this study lies in its targeted evaluation of established Landsat-8 band-ratio models for eutrophication monitoring in a small, optically complex reservoir. Rather than proposing new spectral indices, this study systematically assesses the applicability, robustness, and limitations of commonly used band-ratio approaches when applied to a spatially constrained and highly eutrophic waters. Specifically, this study aims to: (1) develop an empirical model for estimating TSI values from L8-derived remote sensing reflectances; (2) apply the model to a time series of L8 images acquired between July 2021 and July 2025 to characterize the spatial and temporal dynamics of eutrophication; and (3) examine the relationship between the observed trophic conditions and surrounding land use patterns within the reservoir catchment. By focusing on a small-reservoir context, this study provides methodological insights and practical guidance for cost-effective eutrophication monitoring and management of vulnerable freshwater resources.

2. METHODOLOGY

2.1 Study area

XKR is an artificial freshwater body in Son Tay Town, Hanoi, Vietnam, constructed in 1964 for irrigation and aquaculture (Figure 1). It covers approximately 60 ha with an average depth of 2-4 m and is strongly influenced by the regional monsoonal climate, with inflows dominated by agricultural runoff and small tributaries. The reservoir water level is primarily regulated by local management, often maintained at relatively low levels during the

summer to accommodate heavy rainfall and reduce flood risk, and raised toward the end of the year (November-December) to store water for the subsequent winter-spring agricultural season. This

direct land-water connection makes the reservoir highly sensitive to nutrient and sediment loading from surrounding land-use.

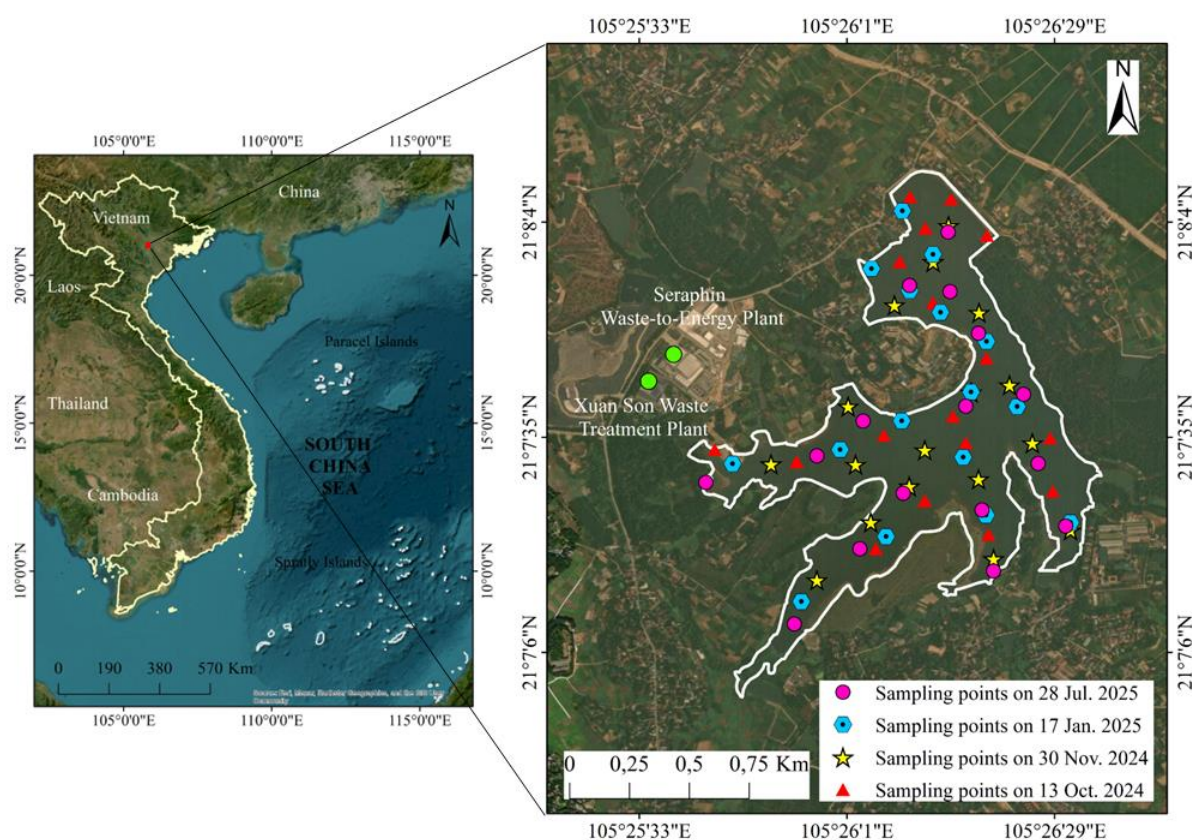


Figure 1. Locations of Xuan Khanh Reservoir in Vietnam and distribution of sampling points.

Over decades of use, the reservoir has shown increasing signs of eutrophication, including high turbidity, recurrent algal blooms, organic enrichment, and sediment accumulation (Gusev et al., 2021; Tran et al., 2021). Its proximity to the Xuan Son Waste Treatment Complex further raises concerns about nutrient and contaminant influxes from wastewater leakage (The Kha, 2018; Nguyen Hoai, 2019). In addition, the reservoir has been identified as a potential habitat for *Rafetus swinhoei*, the critically endangered Hoàn Kiếm Turtle (Bettelheim, 2012), underscoring its global biodiversity significance (Seimon et al., 2024). The combination of ecological importance and exposure to multiple anthropogenic pressures, particularly untreated or partially treated wastewater inputs rich in nutrients and organic matter, highlights the urgent need for frequent eutrophication monitoring. Despite these pressures, no systematic assessment of its trophic status has been conducted, leaving a critical gap for management and conservation. Given its ecological vulnerability and

socio-economic importance, XKR provides a representative case study for evaluating the feasibility of using L8 to monitor eutrophication through TSI estimation and mapping.

2.2 Water sampling and measurement

Field surveys at XKR were conducted on four occasions: 13 October 2024, 30 November 2024, 17 January 2025, and 28 July 2025. These campaigns were scheduled to coincide with L8 overpasses during periods of minimal cloud cover, ensuring that in-situ measurements could be directly matched with satellite observations. To enhance temporal consistency, sampling was carried out within approximately one hour before or after the satellite overpass. In total, 66 surface water samples were collected across the campaigns. Sampling points were systematically distributed throughout the reservoir (Figure 1) to represent spatial variability in water quality (Karabork, 2010). At each location, the geographic position was recorded with a handheld GPS, water

transparency (SDD) was measured using a Secchi disk, and surface water was collected for laboratory analysis.

Samples were taken from the upper 0-30 cm of the water column, representing the photic zone where phytoplankton dynamics and external nutrient inputs exert the strongest influence. Chla concentrations were analyzed following the Standard Methods for the Examination of Water and Wastewater (APHA, 1998). Accordingly, water samples were filtered through Whatman 7184-004 cellulose nitrate membrane filters (pore size 0.45 μm ; diameter 47 mm) to retain phytoplankton. The material on the filters was extracted in 90% acetone to release pigments. Chla concentrations in the extracts were then determined spectrophotometrically using a DR 6000 UV-VIS spectrophotometer (Hach, USA; spectral bandwidth 1 nm) with matched 25.4 mm cuvettes. The Chla concentration in water samples was calculated as:

$$\text{Chla } (\mu\text{g/L}) = \frac{C_a \times V_1}{V_0} \quad (1)$$

Where; V_1 is the extract volume (L), V_0 is the sample volume (m^3), and C_a is the concentration of Chla in the extract, determined by:

$$C_a = 11.85 \times D_{664} - 1.54 \times D_{647} - 0.08 \times D_{630} \quad (2)$$

Where; D_{630} , D_{647} , D_{664} are the optical densities measured at wavelengths of 630 nm, 647 nm, and 664 nm, respectively.

2.3 TSI calculation and model development

The trophic status of each sampling site was evaluated using Carlson's TSI, calculated from in-situ Chla and SDD. This approach follows the method originally proposed by Carlson (1977) and later refined by Carlson and Simpson (1996). According to this classification, a lake is considered oligotrophic when mean TSI values are <30, mesotrophic when 30-50, slightly eutrophic at 50-60, highly eutrophic at 60-70, and hypereutrophic when values exceed 70 (typically approaching 100). The TSI value at each sampling point was determined using the following equations:

$$\text{TSI} = \frac{\text{TSI}_{(\text{Chla})} + \text{TSI}_{(\text{SDD})}}{2} \quad (3)$$

$$\text{TSI}(\text{Chla}) = 9.81 \cdot \ln(\text{Chla}) + 30.6 \quad (4)$$

$$\text{TSI}(\text{SDD}) = 60 - 14.41 \cdot \ln(\text{SDD}) \quad (5)$$

Where; Chla is expressed in $\mu\text{g/L}$ and SDD in meters. All TSI values are unitless.

To extend this approach using remote sensing, we developed an empirical model for estimating TSI from L8 imagery. First, correlations between in-situ TSI values and L8-derived spectral reflectance at corresponding sampling points were examined to identify effective band ratios or combinations. Model calibration was performed using 50 paired observations collected during three campaigns (13 October 2024, 30 November 2024, and 17 January 2025). An independent dataset of 16 samples from 28 July 2025 was used for validation, allowing assessment of model transferability across different seasonal and trophic conditions.

A set of linear and non-linear regression models was constructed to characterize the relationships between selected band indices and TSI. The optimal model was selected based on statistical performance indicators, including Pearson's correlation coefficient (r), coefficient of determination (R^2), and root mean square error (RMSE), evaluated for both calibration and validation datasets at a significance level of $p < 0.05$. The validated model was then applied to a time series of 19 L8 images acquired between July 2021 and July 2025 to generate spatially explicit maps of seasonal and interannual TSI variability in XKR.

2.4 L8 image processing and mapping method

A total of 19 L8 scenes (path 127, row 45) covering Hanoi, Vietnam, were obtained from the USGS Earth Explorer portal (<https://earthexplorer.usgs.gov/>). Details of the selected images are provided in Table 1. All scenes correspond to Level-2A products, which provide atmospherically corrected surface reflectance generated using the Land Surface Reflectance Code (LaSRC) algorithm (Vermote et al., 2016). The use of LaSRC-based reflectance (hereafter L8-LaSRC) was motivated by its demonstrated reliability for inland water quality monitoring (Bernardo et al., 2017; Pham et al., 2018; Allam et al., 2020; Vinh et al., 2022), combined with its accessibility and computational efficiency.

Accordingly, all L8-LaSRC images were inspected for cloud contamination, and only cloud-free or minimally cloudy scenes were retained (Table 1). The Modified Normalized Difference Water Index (MNDWI) was then applied to delineate water bodies and mask out land areas (Xu, 2006). This step

ensured that only pure water pixels within the reservoir were included in the analysis.

For calibration purposes, spectral reflectance values corresponding to in-situ sampling locations were extracted using ENVI 5.3. Four field-validated

images, coinciding with the water sampling campaigns, were used to establish relationships between L8 band ratios/indices and TSI values. These relationships were used to calibrate empirical regression models.

Table 1. List of L8 scenes used for mapping, calibration, and validation of TSI in XKR

Purpose	Landsat product identifier (Path 127/Row 45)	Acquisition date	Notes
Mapping	LC08_L2SP_127045_20210717_20210729_02_T1	17/07/2021 - 22/03/2025	Used to produce time-series TSI maps
	LC08_L2SP_127045_20210818_20210827_02_T1		
	LC08_L2SP_127045_20211005_20211013_02_T1		
	LC08_L2SP_127045_20220704_20220707_02_T1		
	LC08_L2SP_127045_20220906_20220914_02_T1		
	LC08_L2SP_127045_20221024_20221101_02_T1		
	LC08_L2SP_127045_20221109_20221121_02_T1		
	LC08_L2SP_127045_20230504_20230509_02_T1		
	LC08_L2SP_127045_20230707_20230718_02_T1		
	LC08_L2SP_127045_20231027_20231101_02_T1		
	LC08_L2SP_127045_20231128_20231208_02_T1		
	LC08_L2SP_127045_20231214_20240102_02_T1		
	LC08_L2SP_127045_20240420_20240429_02_T1		
	LC08_L2SP_127045_20240810_20240815_02_T1		
	LC08_L2SP_127045_20250322_20250327_02_T1		
Calibration	LC08_L2SP_127045_20241013_20241021_02_T1	13/10/2024, 30/11/2024, 17/01/2025	Matched with in-situ measurements for model calibration
	LC08_L2SP_127045_20241130_20241203_02_T1		
	LC08_L2SP_127045_20250117_20250127_02_T1		
Validation	LC08_L2SP_127045_20250728_20250807_02_T1	28/07/2025	Independent dataset for model validation

Then, the optimal regression model was applied to all 19 cloud-free L8 images acquired between July 2021 and July 2025 to estimate TSI across the reservoir. Pixel-level TSI values were computed and aggregated into thematic maps, allowing the visualization of eutrophication patterns. The results were classified into 18 Jenks classes to highlight spatial gradients of trophic status and to adequately represent the high spatial variability within this small reservoir.

Finally, in addition to spatial mapping, estimated TSI values from the 19 scenes were analyzed to identify seasonal and interannual variations. This approach provided insights into both the temporal dynamics of eutrophication and the influence of hydrological seasonality and external inputs. The overall workflow, from in-situ data collection and model calibration to the mapping of TSI distribution from L8 imagery, is summarized in [Figure 2](#).

3. RESULTS

3.1 Water quality and trophic status of Xuan Khanh Reservoir

[Figure 3](#) shows temporal variations in Chla, SDD, and TSI in XKR across four sampling periods (October 2024, November 2024, January 2025, and July 2025). Accordingly, Chla in the reservoir water displayed pronounced seasonal fluctuations. The highest levels were observed in October 2024, with a mean of ~108 µg/L and extreme values exceeding 180 µg/L, indicating severe algal proliferation at the onset of autumn. Concentrations declined sharply by late November (~57 µg/L), accompanied by reduced variability, suggesting a temporary reduction in algal biomass. The lowest mean values were recorded in January 2025 (~40 µg/L), although variability was wide (27-88 µg/L), pointing to spatially heterogeneous conditions during winter. By July 2025, Chla increased again (mean ~65 µg/L), reflecting moderate

but persistent algal activity during the summer. This seasonal cycle highlights a typical pattern of autumn

algal blooms, winter decline, and summer resurgence linked to nutrient dynamics and stratification.

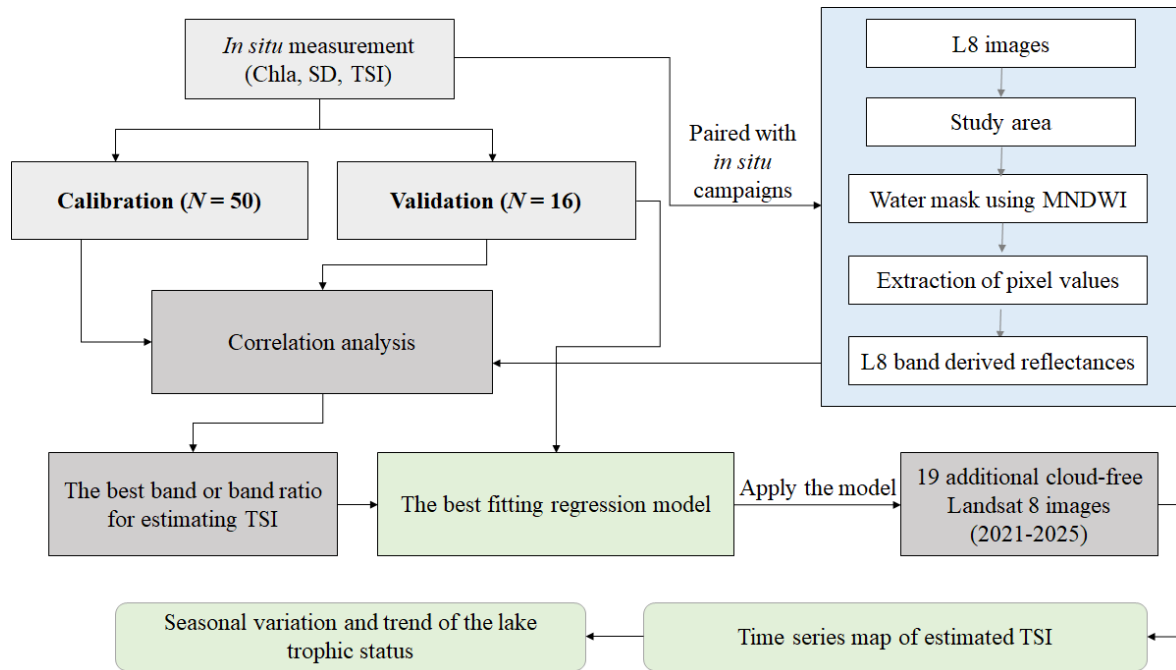


Figure 2. Workflow for estimating and mapping the Trophic State Index (TSI) in XKR using Landsat 8 imagery, integrating in-situ data, model calibration/validation, and time-series analysis. MNDWI refers to the Modified Normalized Difference Water Index.

Consistent with these patterns, SDD showed an inverse response to seasonal changes in Chla, confirming the inverse relationship between algal biomass and water clarity. Across all sampling campaigns, Chla was negatively correlated with SDD ($r=-0.85$, $p<0.01$), confirming that phytoplankton biomass is the dominant driver of transparency in the reservoir. This negative relationship reflects the typical eutrophic condition, where elevated algal growth consistently reduces light penetration. SDD was poorest in October 2024 (mean ~ 0.33 m), coinciding with the peak bloom, and improved markedly by November (~ 0.67 m) and January (~ 0.73 m), when algal concentrations were lower. In July 2025, SDD declined again (~ 0.43 m), reflecting reduced clarity due to renewed algal growth and possibly higher suspended solids during the wet season.

The trophic state of the reservoir, expressed as TSI, remained consistently in the eutrophic to hypereutrophic range across all four surveys. Both TSI (Chla) and TSI (SDD) were highest in October 2024 (means ~ 73 -75), clearly above the hypereutrophic threshold (>70). Although lower in November and January (means ~ 66 -69), values still indicated eutrophic to highly eutrophic conditions. By July

2025, TSI values increased again (~ 72), reflecting renewed eutrophication pressure during midsummer. These results demonstrate that XKR is persistently eutrophic, with episodic shifts into hypereutrophic conditions, driven largely by algal blooms and fluctuating transparency.

Based on the field datasets collected during the four surveys shown in Figure 3, the measurements from 13 October 2024, 30 November 2024, and 17 January 2025 exhibited wide ranges of Chla, SDD, and TSI values, making them appropriate for constructing the calibration dataset. In contrast, the dataset from 28 July 2025 displayed a narrower distribution of these parameters and was therefore used as an independent dataset to verify model performance under a different seasonal context with distinct climatic characteristics.

3.2 Model to estimate the Trophic State Index (TSI)

Figure 4 shows L8 band-based remote sensing reflectance spectra, $L8\text{-}LaSRC R_{rs}(\lambda)$, derived from 66 sampling points, representing two contrasting hydrological seasons (wet and dry). Clear temporal differences in optical properties were observed across the seven spectral bands. In October, water reflectance was consistently higher, particularly in the green (B3) and near-infrared (B5) bands, indicating elevated

turbidity or suspended particulate matter during the wet season. By contrast, spectra from November and January displayed lower and more uniform reflectance across all bands, consistent with clearer water and reduced phytoplankton biomass. These seasonal differences align with earlier findings that water reflectance increases during periods of algal proliferation or high nutrient loading (Wang et al., 2025; Kiwanuka et al., 2025b). The reduced variability and subdued reflectance in the cooler, drier months

further support the interpretation of enhanced water clarity when algal growth is constrained by lower temperatures and nutrient availability. Unlike the L8 band-based spectra typically observed in marine and coastal waters (Yan et al., 2023), the L8-LaSRC $R_{rs}(\lambda)$ spectra of XKR water show a distinct peak in the near-infrared band (B5), indicative of high phytoplankton biomass and suspended matter in the water column, as also reported by Ha et al. (2022) and Ha et al. (2024).

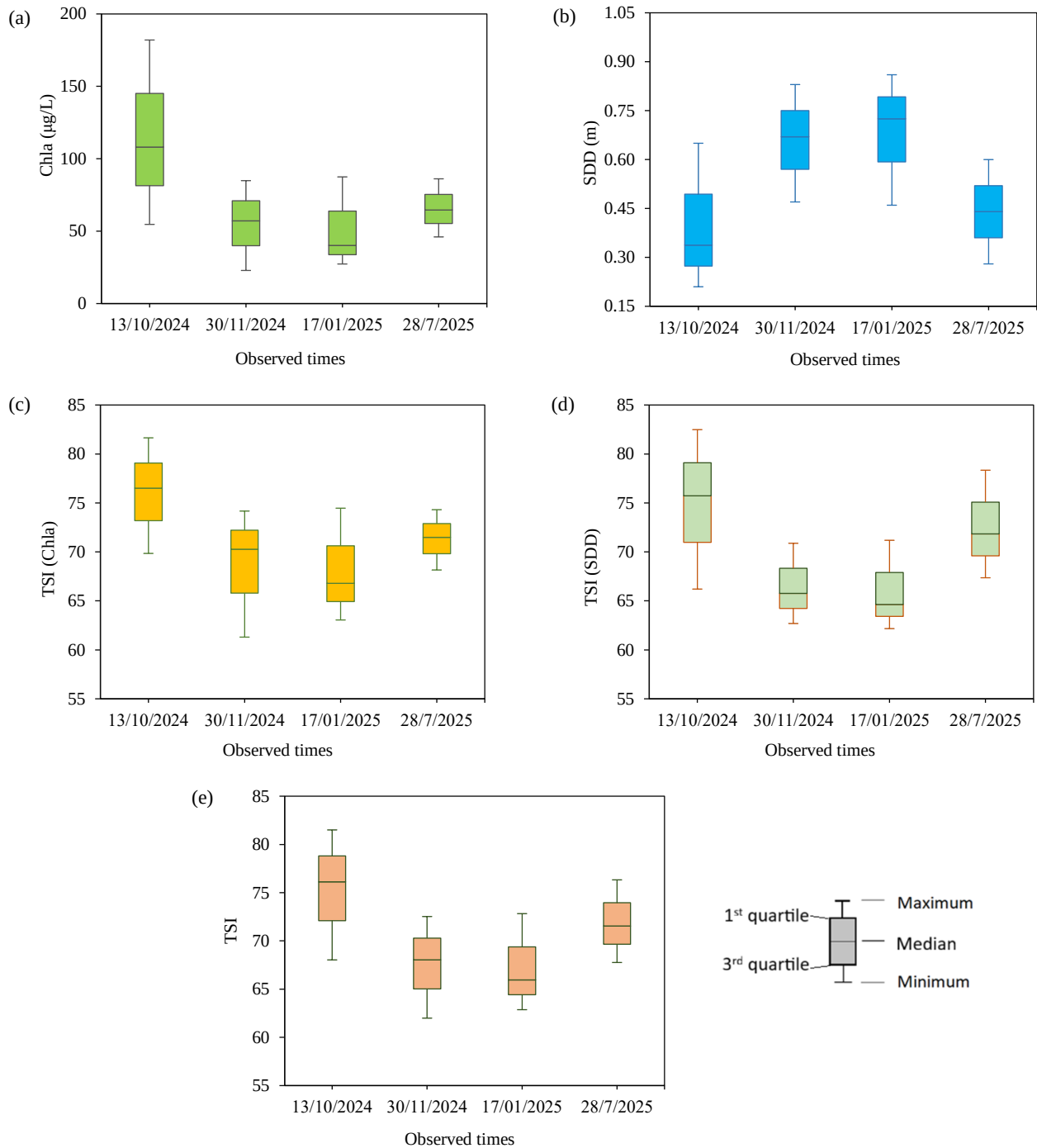


Figure 3. Temporal variations of chlorophyll-a (Chla) (a), Secchi disk depth (SDD) (b), TSI(Chla) (c), TSI(SDD) (d), and overall TSI (e) in XKR based on four field campaigns (13 October 2024, 30 November 2024, 17 January 2025, and 28 July 2025).

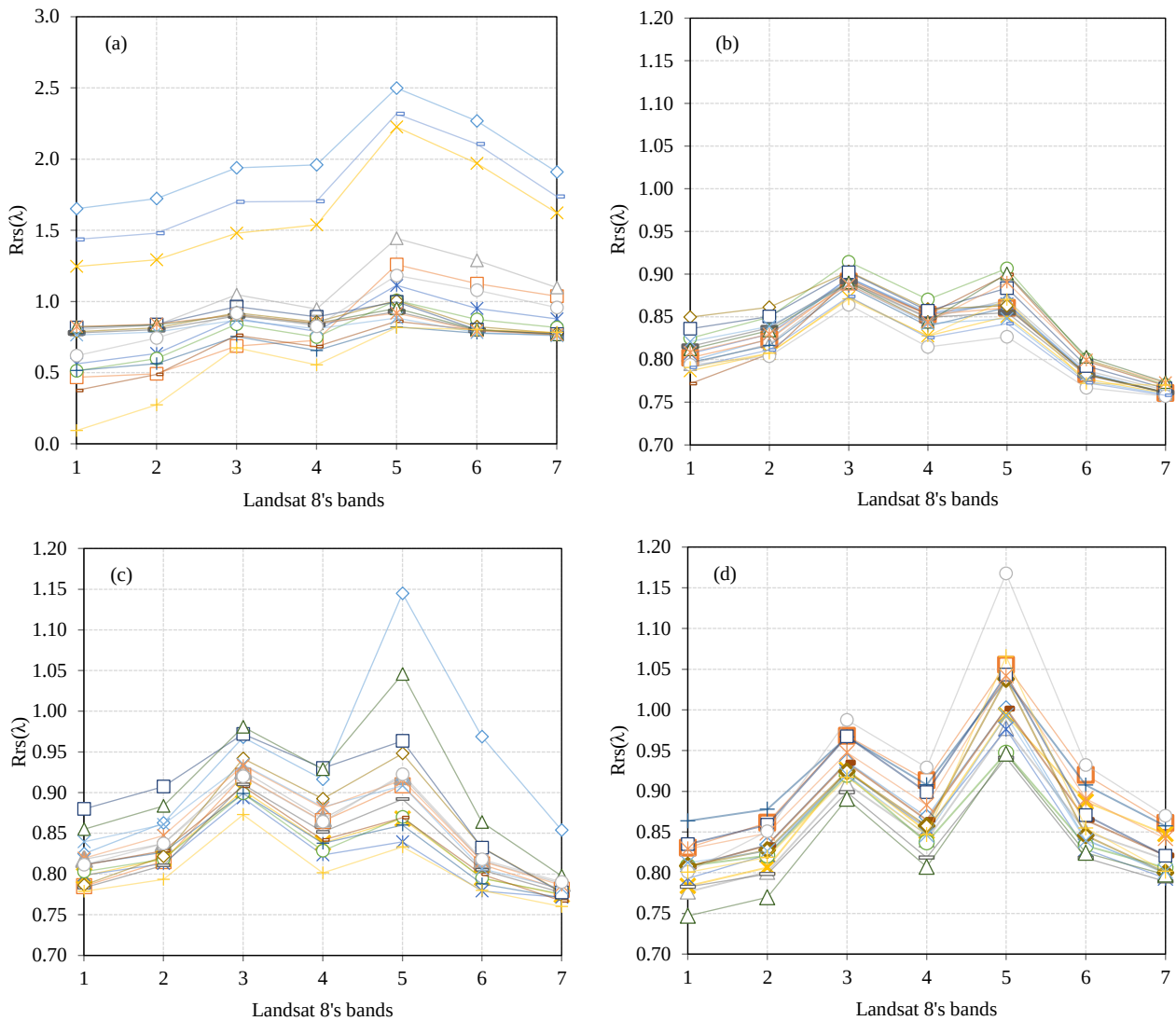


Figure 4. The Landsat 8 band-based reflectance spectra of water at sampling points were obtained on the following dates: a) October 13, 2024 (N=17); b) November 30, 2024 (N=17); c) January 17, 2025 (N=16) and d) July 28, 2025 (N=16). The bands are labeled as B1 to B7 corresponding to band 1 to band 7 of the Landsat 8 imagery.

Figure 5(a) illustrates the correlations between Chla, SDD, and Landsat-8 single bands and band ratios using data from all four campaigns. Chla exhibits consistently positive correlations with band ratios involving the red-edge and red bands, particularly B5/B4 ($r=0.89$) and B5/B3 ($r=0.85$), indicating sensitivity to phytoplankton-related scattering and absorption features. In contrast, SDD shows strong negative correlations with several band ratios, reflecting the inverse relationship between water transparency and optically active constituents. These results indicate that band-ratio combinations tend to provide stronger and more consistent relationships than single bands. The relationships between in-situ TSI and L8-LaSRC $R_{rs}(\lambda)$ values were also investigated (Figure 5(b)). Overall, TSI showed weak and inconsistent correlations with individual

spectral bands, with the exception of January, when stronger relationships emerged ($r=0.81$ for B6; $r=0.78$ for B5). This suggests that the shortwave infrared (B6) and near-infrared (B5) regions are more sensitive to trophic variations under cooler, clearer-water conditions. In contrast, October and November datasets yielded weaker correlations, particularly in the visible range (B1-B4), likely due to high turbidity masking algal signals. When all seasons were pooled, only moderate correlations were observed in B5 ($r=0.54$) and B6 ($r=0.51$), indicating that no single band consistently captured TSI dynamics. These results demonstrate that single-band approaches are inadequate for XKR, and that multi-band or band-ratio algorithms are more appropriate for estimating TSI under variable optical conditions.

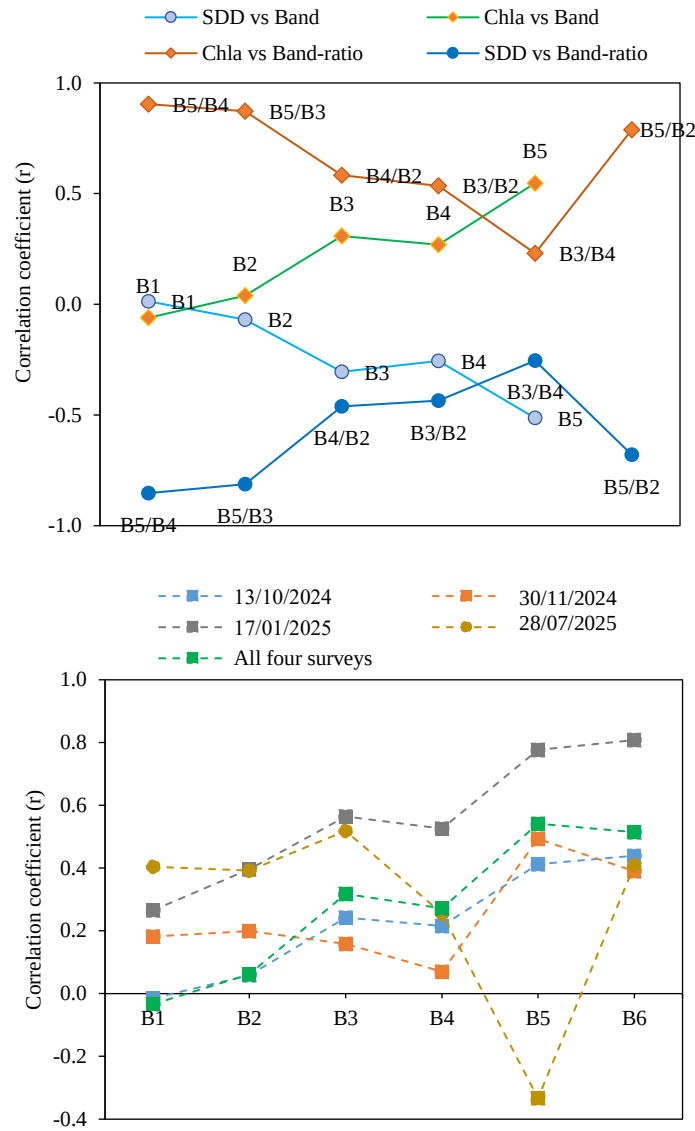


Figure 5. The correlations between Chla and SDD with Landsat 8 bands and band-ratios using data from all four campaigns (a), and between TSI with Landsat 8 bands (b)

Six L8 band ratios were tested against in-situ TSI values (Figure 6). Among the models evaluated, exponential regressions generally produced lower errors than linear or logarithmic fits, consistent with previous findings on trophic state modeling (Ha and Koike, 2011). The NIR-to-red ratio (B5/B4) showed the strongest performance ($R^2=0.80$, $RMSE=0.04$), followed closely by the NIR-to-green ratio (B5/B3; $R^2=0.73$, $RMSE=0.04$). Both indices highlight the effectiveness of NIR-involved ratios in capturing chlorophyll-related signals. In contrast, the green-to-red (B3/B4) and green-to-blue ratios (B3/B1, B3/B2) yielded weak to moderate correlations ($R^2 \leq 0.27$), indicating limited predictive value in this dataset. The blue-to-NIR ratio (B2/B4) displayed a moderate

negative relationship with TSI ($R^2=0.44$). Overall, these results confirm that band ratios incorporating NIR bands, particularly B5/B4, are the most suitable for estimating trophic status in XKR.

Accordingly, the NIR-to-red ratio (B5/B4) was identified as the most effective predictor of TSI in XKR. An exponential regression model was fitted to describe the relationship, which is expressed as:

$$TSI = 40.8 \times e^{0.48 \frac{B5}{B4}} \quad (6)$$

Where; B5 and B4 represent the remote sensing reflectance $R_{rs}(\lambda)$ from the NIR and red bands of L8-LaSRC, respectively.

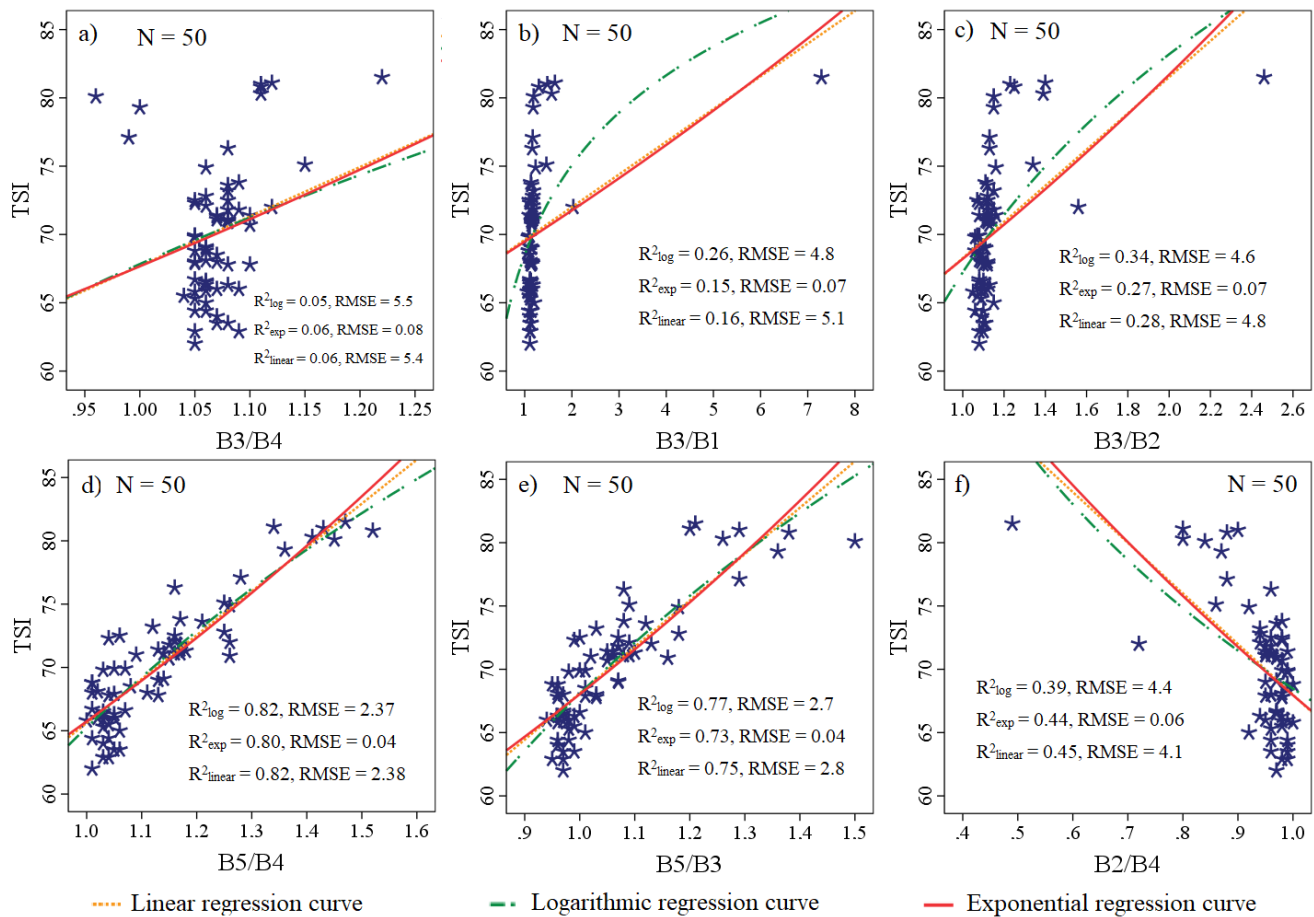


Figure 6. Cross-relationships of in-situ TSI and L8-LaSRC band ratio-based reflectances as commonly used to estimate TSI in the reviewed literature: a) green-to-red band ratio; b-c) green-to-blue band ratios; d) NIR-to-red band ratio; e) NIR-to-green band ratio; and f) blue-to-NIR band ratio. Abbreviations of the L8-LaSRC band 1 to band 5 corresponded to B1 to B5.

Model performance was evaluated using both calibration ($N=50$) and independent validation ($N=16$) datasets, which together encompassed a wide range of measured TSI values. The results demonstrated strong predictive ability, with calibration yielding $R^2=0.81$ and $RMSE=2.4$, and validation producing $R^2=0.63$ and $RMSE=1.6$ (Figure 7). The lower validation R^2 likely reflects increased temporal variability in water quality conditions across sampling campaigns, combined with the limited size of the independent validation dataset. When the datasets were combined ($N=66$), the overall performance was robust, achieving $R^2=0.81$ and $RMSE=2.2$, corresponding to only $\sim 2.5\%$ of the mean in-situ TSI. These results confirm the reliability and robustness of the proposed model for quantifying trophic status in XKR under varying seasonal and trophic conditions.

3.3 Spatial-temporal distribution of the trophic state index

Equation (6) was applied to 19 L8-LaSRC images acquired between July 2021 and July 2025 to

investigate spatial and seasonal variations in TSI across XKR. As shown in Figure 8, TSI values ranged from 64.1 (18 August 2021) to 82.0 (20 April 2024), with mean values spanning 65.1 to 75.1 over the study period, and peak TSI values consistently occurring during bloom-prone months in summer (July–September) and early spring (April). According to the trophic classification of Carlson and Simpson (1996), the reservoir consistently remained in a highly eutrophic to hypereutrophic state, with pronounced seasonal fluctuations.

Spatial patterns revealed marked heterogeneity across different parts of the reservoir. The shallow northern and northeastern zones persistently exhibited elevated TSI values, particularly during bloom-prone months, likely reflecting restricted circulation and nutrient accumulation. By contrast, the deeper central and southern zones generally maintained lower TSI, indicative of greater mixing and dilution capacity. Episodic hotspots of hypereutrophy ($TSI > 74$) were detected, especially in July 2022, April 2024, and July 2025, with peak values concentrated near inflow areas

where external nutrient inputs are greatest. Notably, in April 2024, large portions of the northern basin reached TSI values up to 78, signaling severe eutrophication and potential harmful algal bloom development. These findings suggest that eutrophication in XKR is spatially heterogeneous, with localized hotspots driven by hydrological inputs and basin morphology rather than uniform reservoir-wide processes.

Figure 9 shows temporal fluctuations in the trophic status of XKR from July 2021 to July 2025. TSI values ranged between ~64 and 82, with most observations concentrated near the eutrophic-hypereutrophic threshold (TSI~70). This indicates that the reservoir consistently shifted between highly eutrophic and hypereutrophic conditions, with strong seasonal variability. Peaks in TSI were recorded during the summers of 2022, 2024, and 2025, when values exceeded 74, reflecting intensified phytoplankton growth under warm and stratified conditions. By contrast, lower TSI values were

observed in late 2021, mid-2023, and early 2025, suggesting temporary reductions in trophic status.

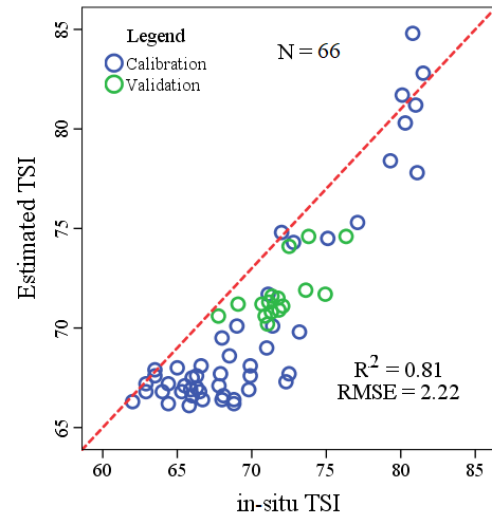


Figure 7. Relationships between in-situ and estimated TSI for both model calibration (N=66; $R^2=0.81$; RMSE=2.4) and validation (N=16; $R^2=0.63$; RMSE=1.6) datasets by the Equation (6)

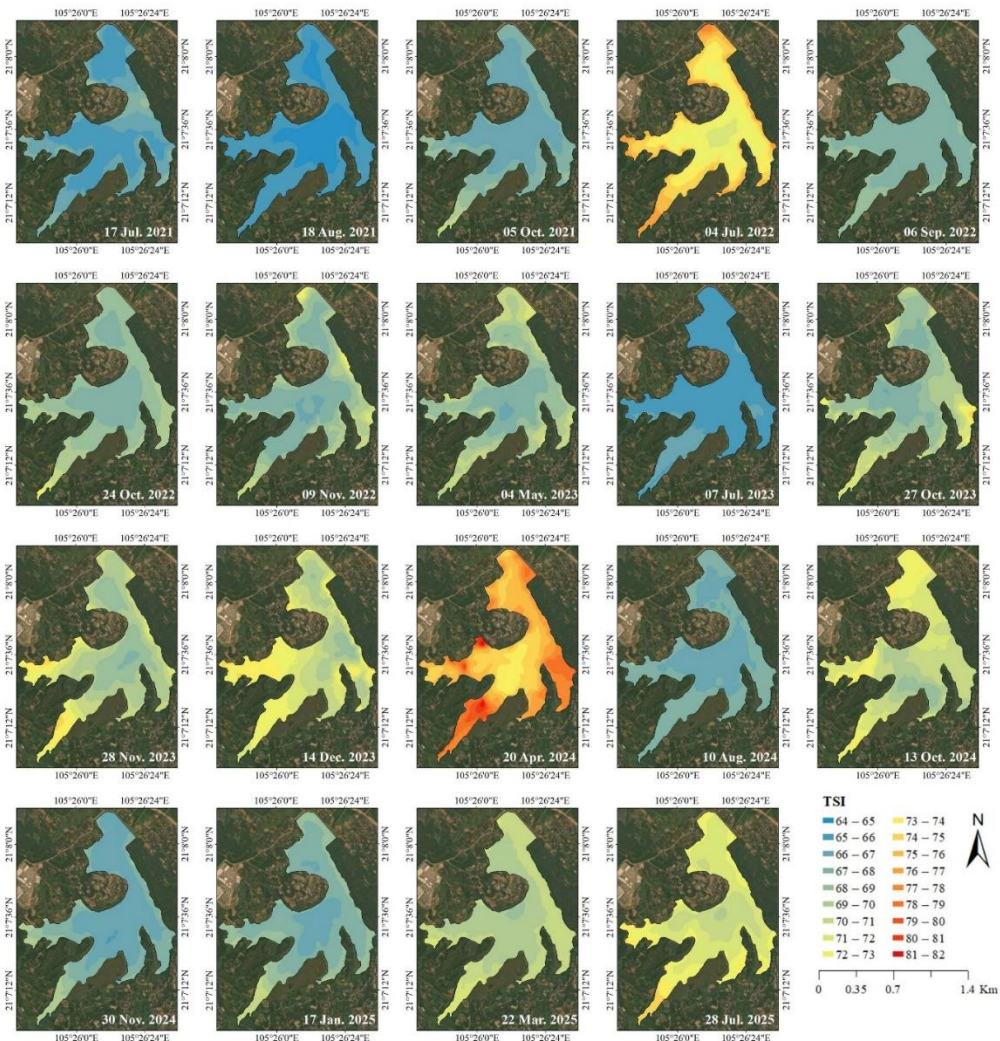


Figure 8. Spatial distribution of TSI in XKR estimated from 19 L8-LaSRC scenes acquired from July 2021 to July 2025.

Spatial heterogeneity was also evident, with boxplot ranges varying considerably between sampling times. Wider ranges, such as those in September 2022 and August 2024, indicate localized algal blooms or uneven nutrient loading across the reservoir. Interannual variability was particularly clear in July: values in 2021 were relatively low (TSI=66),

increased sharply in 2022 (TSI ~75), declined slightly in 2023 (TSI=68), and rose again in 2025, when values consistently exceeded the hypereutrophic threshold. Overall, these results demonstrate both the seasonal and interannual instability of trophic conditions in XKR.

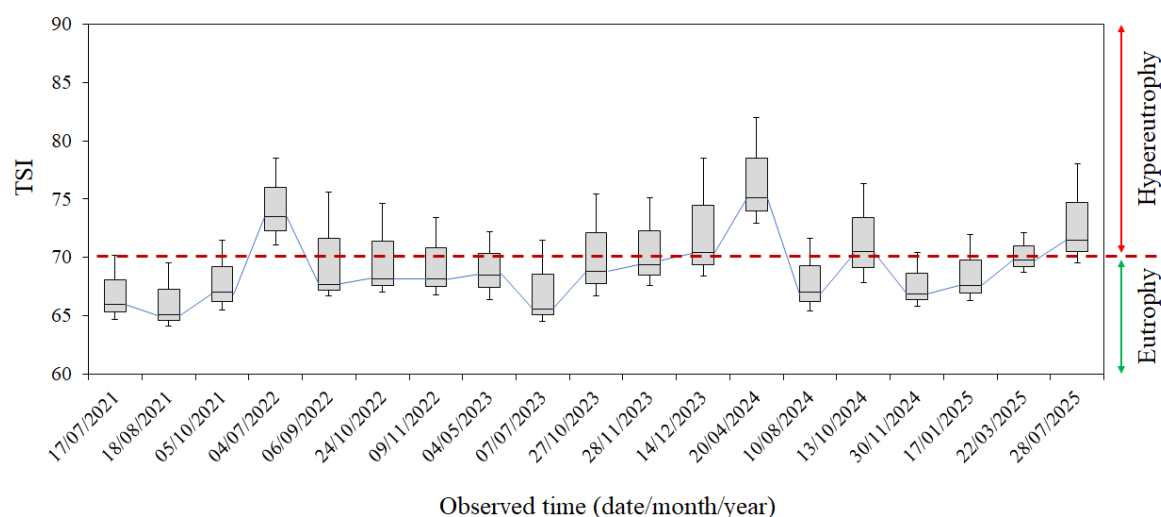


Figure 9. Temporal variations of TSI obtained from 19 L8-LaSRC images

4. DISCUSSION

Our results demonstrate that freely available L8 imagery provides a practical and reliable tool for monitoring eutrophication in small, polluted reservoirs. Despite the relatively coarse 30-m resolution, the calibrated B5/B4 model produced strong agreement with in-situ TSI, showing that Landsat data can capture both seasonal variation and spatial heterogeneity in trophic conditions. This is particularly relevant for reservoirs such as XKR, where continuous field monitoring is limited but management decisions require frequent information.

The strong performance of the NIR-to-red ratio (B5/B4) in this study confirms its suitability for monitoring eutrophication in small, algae-rich reservoirs. Previous research has demonstrated the robustness of this index for estimating Chla in turbid and productive freshwater systems using L8 imagery (Watanabe et al., 2015; Boucher et al., 2018; Markogianni et al., 2018; Lai et al., 2021), and our findings extend its applicability to XKR. Here, Chla was found to be the principal driver of trophic conditions, with TSI showing an exceptionally strong correlation with Chla ($r=0.95$). This direct linkage explains why the B5/B4 ratio, which is highly sensitive to Chla dynamics, also performs well in

estimating TSI in the reservoir. The effectiveness of B5/B4 arises from the pronounced absorption of Chla in the red band and the elevated reflectance of phytoplankton in the NIR region, which together enhance sensitivity to algal biomass. Moreover, the index is comparatively less influenced by suspended sediments than blue- or green-based ratios, which are more susceptible to scattering by non-algal particles. This makes the NIR-to-red ratio particularly advantageous in environments such as XKR, where eutrophication is driven by recurrent phytoplankton blooms but water optical properties are periodically altered by runoff-derived suspended matter from the surrounding catchment.

When compared with previous studies, the performance of our B5/B4 model ($R^2=0.81$; $RMSE=2.2$, corresponding to ~2.5% of average in-situ TSI) is consistent with, or in some cases superior to, results reported for other inland waters. For example, Watanabe et al. (2015) achieved $R^2=0.75$ for TSI(Chla) in the Barra Bonita Reservoir using the NIR-to-red ratio, while Vinh et al. (2022) reported $R^2=0.65$ for TSI estimation in urban lakes in Hanoi with a NIR-to-green ratio. In China, Hu et al. (2021) applied the Algal Bloom Index (ABI) from L8 visible bands to 146 lakes and achieved $R^2=0.57-0.62$

depending on turbidity conditions, and Zhou et al. (2019) used a radial basis function neural network with L8 band ratios to estimate TLI, obtaining $R^2=0.73$. Against this backdrop, our results demonstrate that L8-based empirical models can achieve comparably high or even superior accuracy in a small, polluted reservoir where trophic status is strongly dominated by algal dynamics, underscoring the robustness of the NIR-to-red ratio for eutrophication monitoring. These findings suggest that the B5/B4 ratio is particularly suitable for calculating TSI at the scale of individual, highly productive lakes or reservoirs. Nevertheless, its broader applicability across regional lake networks may be limited, since water bodies influenced by high concentrations of inorganic suspended matter or colored dissolved organic matter often exhibit weaker correlations with this index. Differences between these studies and the present work may be partly attributed to variations in water body optical properties and trophic conditions, as several previous studies focused on hypereutrophic lakes or active algal bloom events, whereas XKR is characterized by a high eutrophic state. In addition, discrepancies may also arise from differences in methodological approaches, as empirical band-ratio models, such as those applied here, can respond differently to optical variability compared with machine-learning-based methods.

The spatial distribution of TSI derived from 19 images revealed persistent hotspots in the northern and northeastern zones of the reservoir. These areas

correspond closely with inflow channels draining agricultural land and the vicinity of the Xuan Son Waste Treatment Complex (Figure 10). The alignment of high TSI zones with these land uses suggests that both diffuse nutrient runoff and point-source discharges are major external drivers of eutrophication in XKR. Peaks observed in summer months further emphasize the interaction between catchment pressures and seasonal hydrological and thermal regimes.

Despite the promising results, several limitations of this study should be acknowledged. First, the TSI retrieval model was based on an empirical approach, calibrated with a limited number of in-situ measurements. While the B5/B4 ratio showed strong correlations with trophic status, empirical models are site-specific and may have limited transferability to other reservoirs with different optical properties or land-use settings. Second, data availability constrained temporal resolution: only four field campaigns were conducted for calibration and validation, and the use of Landsat imagery was restricted by its 16-day revisit cycle and frequent cloud cover, which can obscure key bloom events. Finally, the model did not explicitly separate the effects of phytoplankton and suspended sediments, which may vary seasonally and spatially in a small, runoff-impacted reservoir like XKR. These limitations suggest that future work should integrate multi-sensor observations, higher-frequency monitoring, and semi-analytical or machine-learning approaches to improve robustness and generalizability.

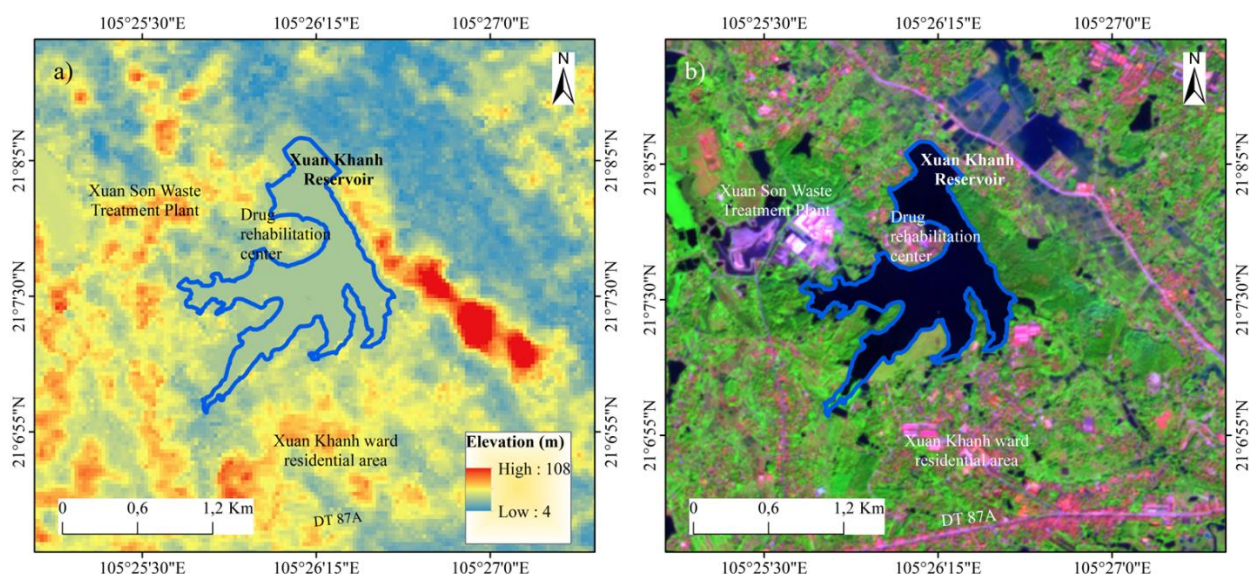


Figure 10. Catchment of XKR showing (a) elevation patterns and (b) major surrounding land uses. Key features include the Xuan Son Waste Treatment Plant, a drug rehabilitation center, and adjacent agricultural and residential areas, all of which represent potential nutrient sources influencing water quality in the reservoir.

Looking ahead, future research should aim to overcome these limitations by combining multi-sensor datasets (e.g., Landsat 8/9, Sentinel-2 MSI, Sentinel-3 OLCI) to improve temporal resolution and reduce cloud-related data gaps. The integration of UAV- or drone-based hyperspectral imagery with satellite observations could also provide higher spatial and spectral detail, helping to disentangle the respective influences of phytoplankton and suspended sediments on reflectance. Moreover, the application of machine learning and semi-analytical approaches has the potential to enhance model robustness, enabling more transferable algorithms for eutrophication monitoring across diverse reservoir systems. Such advancements would provide local managers with more reliable, near-real-time information to support the sustainable management of small, nutrient-enriched reservoirs like XKR.

Although eutrophication indicators can be effectively estimated from satellite imagery, the processes and sources driving eutrophication are strongly influenced by factors such as water-level regulation, microbial dynamics, and reservoir management practices (Li et al., 2019; Oyege et al., 2024; Wen et al., 2025). Future studies would benefit from integrating remote sensing with hydrological and ecological analyses to better resolve these processes.

5. CONCLUSION

This study shows that XKR, a small and heavily impacted freshwater system, has persisted in a highly eutrophic to hypereutrophic state over the past four years, with clear seasonal fluctuations driven by wet-season runoff, wastewater discharges, and land-use pressures in its catchment. By integrating in-situ measurements (66 samples from four campaigns) with Landsat 8-LaSRC reflectance data, we developed a robust band-ratio model ($B5/B4$) that accurately estimated TSI ($R^2=0.80$, $RMSE=0.04$) and successfully captured both spatial heterogeneity and temporal dynamics of eutrophication. While focused on XKR, the reservoir also serves as a representative case of many small, polluted water bodies in rapidly urbanizing and agricultural landscapes. The results highlight not only persistent nutrient enrichment and localized hotspots of trophic stress but also the broader need for integrated management measures-nutrient load reduction, wastewater treatment, land-use regulation, and catchment-scale restoration-to protect freshwater quality. More broadly, this research demonstrates the value of freely available medium-

resolution satellite imagery (Landsat 8/9) as a cost-effective, transferable, and policy-relevant tool for monitoring eutrophication in small tropical reservoirs.

With proper site-specific recalibration, the approach can be scaled to other data-limited regions, supporting both scientific understanding and practical water resource and environmental management worldwide. In practice, the proposed Landsat-based framework could support routine eutrophication monitoring at seasonal to annual scales, providing timely information to guide nutrient management, wastewater control, and early warning of trophic deterioration in small reservoirs.

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AUTHOR CONTRIBUTIONS

Experimental Run and Data Collection: Ngoc TA, Loi DT, Chien NQ; Methodology and Validation: Thao NTP, Manh NV, Ha NTT; Writing-Original Draft Preparation: Thao NTP, Manh NV, Ha NTT; Formal Analysis, Data Curation, and Visualization: Ngoc TA, Loi DT, Chien NQ; Writing-Review and Editing: Thao NTP, Manh NV, Ha NTT; Supervision: Ha NTT.

DECLARATION OF CONFLICT OF INTEREST

The authors have no competing interests to declare that are relevant to the content of this article.

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