

Remote Sensing of Chlorophyll-A Concentrations in a Water Hyacinth-Infested Tropical Headwaters Lake: A Study of Lake Tana, Ethiopia

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Abstract

Intensified agriculture practices contribute to nutrient enrichment in freshwater lakes, causing eutrophication, algal blooms, and water hyacinth infestations. Eutrophication in Lake Tana, the source of the Blue Nile in Ethiopia, necessitates effective monitoring due to rapid infestation of water hyacinths. While traditional monitoring is costly and limited in spatial and temporal coverage, remote sensing offers a promising alternative. This study develops a regression model to estimate Chlorophyll-a (Chl-a) concentration using in situ and remote sensing reflectance data. Field measurements from 143 locations across Lake Tana were used to validate the correlation equations. Results show that the Moderate Resolution Imaging Spectroradiometer (MODIS) in near-infrared reflectance exhibits the strongest linear relationship with in situ Chl-a measurements for August 2016 ($r^2 = 0.53$), December 2016 ($r^2 = 0.56$) and March 2017 ($r^2 = 0.61$). The developed models were validated with a root-mean-square error of 2.76 $\mu\text{g/l}$, 5.89 $\mu\text{g/l}$, and 8.04 $\mu\text{g/l}$ for August, December, and March, respectively. Applying the developed model from 2008–2018, the Chl-a concentration of the lake indicated an increasing trend, likely driven by non-point sources from surrounding watersheds, causing infestation of the lake by hyacinths since 2011. The agreement between MODIS and in situ Chl-a data, coupled with the satisfactory performance of the linear regression model, underscores that developing a regression model for Chl-a estimation from remote sensing in water hyacinth-infested lakes is a useful method in tracking spatiotemporal variations. This study will serve as a foundation for future Chl-a variation studies in Lake Tana and other similar lakes.

Keywords: Chlorophyll-a; estimation model; Lake Tana; MODIS; remote sensing; water hyacinth.

1. Introduction

Elevated Chl-a levels often indicate nutrient enrichment in freshwater lakes, causing eutrophication (Shi et al., 2022). This nutrient overloading, driven by anthropogenic impacts, can lead to harmful algal blooms, infestation of water hyacinths, oxygen depletion, and ecological imbalances (Palmer et al., 2015). While effective management of Chl-a requires substantial data collection, the conventional Chl-a determination

methods are expensive and time-consuming (Gholizadeh et al., 2016). To address these limitations, utilizing remote sensing for water quality assessment has emerged as a highly effective solution for water quality assessment (Bukata, 2013; Odermatt et al., 2012; Tyler et al., 2016). Integrating remote sensing data with limited conventional measurements can significantly enhance monitoring efforts in low-income countries (Andres et al., 2018). Remote sensing techniques offer a valuable means for monitoring Chl-a levels in freshwater lakes, providing comprehensive spatial and temporal data (Bresciani et al., 2011; Wang et al., 2022; Mpakairi et al., 2024). Remote sensing combined with targeted in-situ sampling has proved cost-effective for mapping Chl-a and aquatic vegetation across data-poor regions of Africa and the Middle East (Leggesse et al., 2023). However, not all satellite sensors are suitable for inland water quality monitoring. Satellites with coarse spatial resolution, regardless of their wide coverage, may not efficiently capture small inland water bodies. High resolution sensors, such as those on Sentinel-2 or Landsat 8, are well-suited for these applications (Pahlevan et al., 2019).

In recent years, numerous studies have demonstrated the effectiveness of satellite remote sensing data in mapping and estimating the distribution of Chl-a and water quality parameters in inland waters. Various types of satellite data, including Landsat TM, Landsat ETM+, Landsat-8, Moderate Resolution Imaging Spectroradiometer (MODIS), Medium Resolution Imaging Spectrometer (MERIS), Advanced Very High-Resolution Radiometer (AVHRR), SeaViewing Wide Field-of-view Sensor (SeaWiFS), and Satellite Pour l'Observation de la Terre (SPOT), have been used for this purpose (Womber et al., 2021). Therefore, remote sensing has become a vital tool for estimating Chl-a and water quality parameters globally (Fan et al., 2023; Yang et al., 2022). Furthermore, remote sensing's excellent spatial and temporal coverages make it a key tool in freshwater quality degradation due to the increasing population boom in developing countries (Adjovu et al., 2023; Sheffield et al., 2018).

Remote sensing studies about Chl-a retrieval in water proved an empirical relationship between radiance in bands or band ratios and observed Chl-a concentration (Moges et al., 2017; Wang et al., 2018; Wu et al., 2013). Early studies, such as Moges et al. (2017), utilized satellite-derived reflectance data from sensors like Landsat TM and ETM+ to estimate Chl-a concentrations in freshwater lakes. Their results indicated strong correlations when using band ratios involving blue and green wavelengths, enabling the development of regional-scale water quality monitoring algorithms. Constructing on this, Wang et al. (2024) employed hyperspectral remote sensing to evaluate coastal waters, emphasizing that narrow spectral bands in the red and near-infrared regions significantly enhanced the detection of phytoplankton-induced watercolor changes, particularly in optically complex waters.

Liu et al. (2010) developed a model to estimate Chl-a concentrations based on the ratio of near infrared (NIR) to red reflectance values, reporting a strong correlation with in-situ water sampling data ($R^2 = 0.85$) across a Chl-a concentration range of 5 to 60 mg/m³. This NIR/red band ratio approach has since been applied in other studies, such as Papenfus et al. (2020), who used MODIS satellite imagery to estimate Chl-a concentrations in the Pearl River system. MODIS-Terra offers a higher temporal resolution and greater sensitivity compared to Landsat-7 ETM+ satellite images (Potapov et al., 2008). Additionally, satellite-derived images of Chl-a can be obtained using single or combined band algorithms based on specific spectral regions of reflectance (Danbara, 2014; Kaba et al., 2014; Miller & McKee, 2004; Moges et al., 2017; Wang & Lu, 2010). The models are typically categorized as empirical, semi-empirical, and analytical (Caballero et al., 2022; Chang et al., 2022; Wang et al., 2018). Empirical models establish a direct relationship between apparent optical properties (such as remote sensing reflectance) and inherent optical properties (Chl-a) through statistical analyses like linear and nonlinear regression (White et al., 2025).

Eutrophication in Lake Tana is primarily driven by anthropogenic nutrient inputs, especially nitrogen and phosphorus, originating from point sources like municipal and industrial wastewater discharges and non-point sources such as agricultural runoff, urban stormwater, and atmospheric deposition. These excess nutrients promote algal blooms, oxygen depletion, and ecosystem degradation, and have been identified as key drivers of the rapid spread of invasive water hyacinth in the lake (Mucheve et al., 2022). Since 2011,

pollution has intensified, leading to frequent algal blooms and widespread hyacinth infestation, with a 2015 field assessment estimating coverage at approximately 34,500 hectares (Anteneh et al., 2015), though this figure remains variable. The weed poses serious threats to environmental health, human well-being, and economic development (Gezie et al., 2018). Despite these challenges, few studies have applied remote sensing to monitor Lake Tana's water quality. Existing research has focused on suspended sediment estimation using MODIS-Terra imagery calibrated with limited in-situ data (Wembera et al., 2021), sediment inflow modeling from the Gumara River (Kaba et al., 2014) and water quality trend analysis using Landsat 7 ETM+ imagery (Moges et al., 2017).

Therefore, the objective of this study is to apply MODIS-Terra satellite reflectance to estimate Chl-a concentration over Lake Tana using observation data from 143 sampling locations at 5km grid locations sampled in August, December 2016 and March 2017. This study advances beyond previous Chl-a Landsat-based estimations in Lake Tana, offering a robust comparison with observed data collected spatially covering the entire lake. Particularly, we aim to: (1) develop a linear regression model between in situ Chl-a concentrations and MODIS-Terra remote sensing reflectance, and (2) estimate the temporal variations in Chl-a concentrations over the lake. The study will provide a baseline to directly support the ongoing efforts by governmental and nongovernmental organizations to eradicate water hyacinths from Lake Tana.

2. Materials and Methods

2.1. Study Area

Lake Tana, the headwaters of the Blue Nile, is located in the northwest of the Ethiopian plateaus (Figure 1). Geographically, the lake lies between 11°43'44" North, 37°23'22" East and 12°10'32" North, 37°15'08" East. As the largest freshwater resource in Ethiopia, Lake Tana holds about half of the country's fresh water reserve (McCartney et al., 2010) and covering 20% of the drainage area of the 15,096 km² Lake Tana basin (Setegn et al., 2011). The populations in the rural as well as those nearby towns are highly dependent on incomes from the lake economy, as it serves services such as transportation, hydropower, irrigation, fishing and ecotourism (Wondie, 2012).

The shallow lake with a mean depth of 9 m and a maximum depth of 15 m (Kebedew et al., 2020), is located in a wide depression of the Ethiopian basaltic plateau and is bordered by flood plains that are frequently flooded during the rainy season. These include the Fogera floodplain in the east (mainly by the Gumara and Rib rivers), Dembia floodplain in the north (from the Megech River), and Kunzila floodplain in the southwest (associated with Gilgel Abay, Kelti and Koga rivers). The Lake is bordered by steep rocks in the west and the northwest (McCartney et al., 2010). The lake is fed by more than 40 small streams (Kebede et al., 2006; Rientjes et al., 2011; Wale et al., 2009) and receives 93% of its volume from the major rivers of Gilgel Abay, Gumara, Ribb and Megech (Kebede et al., 2006). Usually, shallow lakes are particularly susceptible to water quality impairment due to their limited water volume, high surface area to depth ratio, and enhanced interaction between sediments and the water column (Ayele & Atlabachew, 2021; Zhang et al., 2022).

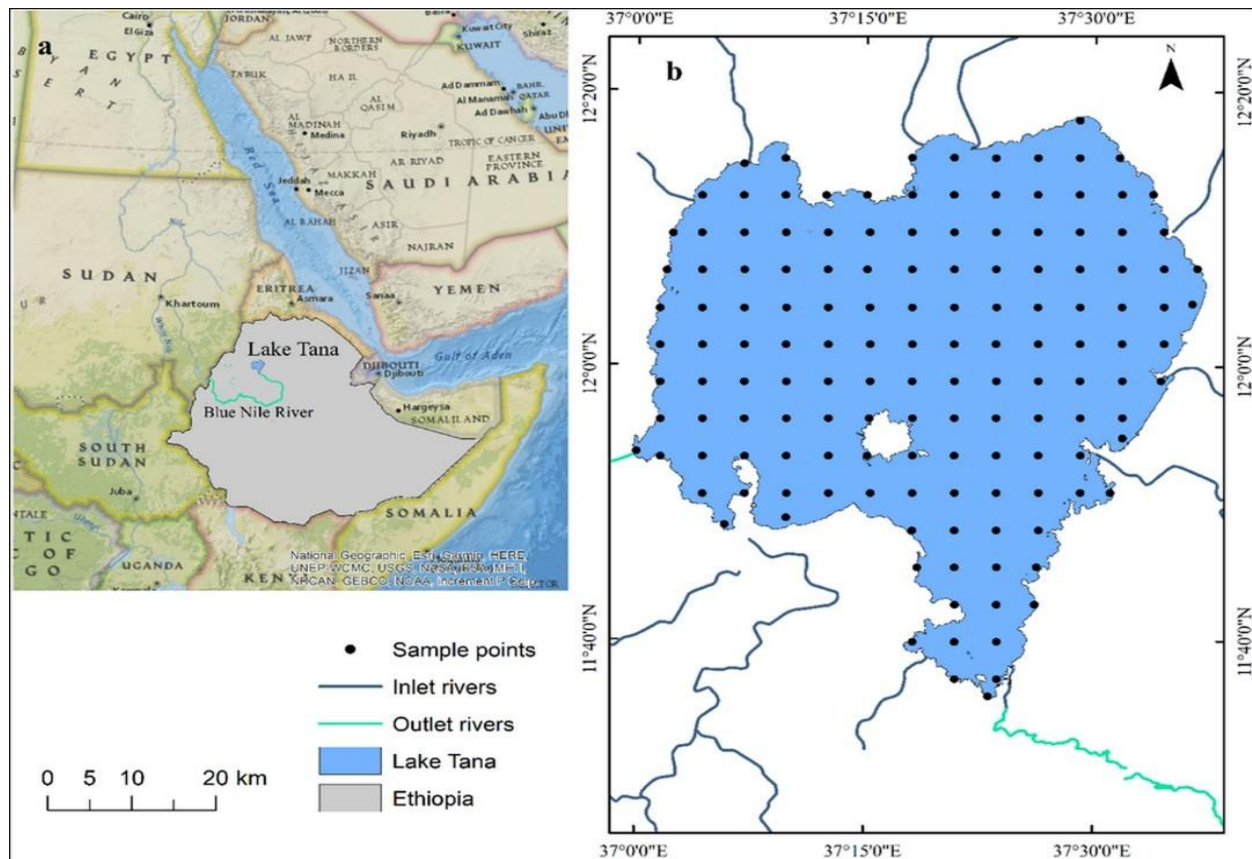


Fig. 1: Location map of the study area: (a) location map of Lake Tana and Ethiopia in the National Geographic World Map and (b) Lake Tana indicating the sample point, inlet and outlet Rivers.

The increasing sediment and nutrient loads from point sources in Bahir Dar town and non-point sources from the agricultural watersheds draining the lake contribute to the decline in water quality (McCartney et al., 2010). Due to agricultural intensification, land use change has occurred over time in the watershed (Biru et al., 2015) transported nutrients into the lake causes the overall water quality deterioration in Lake Tana (Dersseh et al., 2022). As a result, Lake Tana's trophic index level ranged from oligotrophic to hypereutrophic levels and the pollution index status ranged from slightly polluted to polluted annually (Nerae et al., 2024a). Moreover, the annual water quality indices ranged from good to very poor for ecological health and fair to unsuitable for drinking water, with spatially and temporally variability largely influenced by inflow from the tributaries (Nerae et al., 2024b).

2.2. Chl-a Measurement

To determine the spatial and temporal variations of Chl-a measurements in Lake Tana, we used a data set collected and published by Dersseh et al. (2019). Water samples were collected from 143 locations in the lake. The number of samples was determined based on available resources and time constraints, while ensuring careful spatial coverage. Samples were collected three times, in August 2016, December 2016, and March 2017. The coordinates of the sampling locations were determined using a global positioning system (GPS) at a 5 km grid spacing (Figure 1b). Chl-a concentration was determined from the water samples using an acetone extraction method. First, 100 mL of water was filtered through a glass fibre filter. The extract was then centrifuged and extracted overnight with 10 mL of 90% acetone in the dark at 4°C. Absorbance was measured at 750 and 664 nm before and after acidification. The absorbance at 750 nm was used to blank the absorbance at 664 nm. The absorbance at 665 nm was corrected for acidification by adding

one hundred μL of 0.12 N HCl to the extract and waiting 60 seconds. The absorbance at 665 nm and 750 nm was then measured again. Purified Chl-a standards were run to calibrate the spectrophotometer. Chl-a concentration was calculated using the standard methods available in APHA (1998). Further details of the sampling protocol and laboratory determination are described in the cited materials.

2.3. MODIS Terra Data Acquisition and Preprocessing

MODIS-Terra data were selected for their high temporal resolution, long-term continuity, and validated performance in aquatic remote sensing. With daily revisit capability, MODIS improves the chance of cloud-free observations in regions like Lake Tana, where cloud cover limits higher-resolution sensors (Papenfus et al., 2020; Zhou et al., 2023). Despite its coarser spatial resolution (250–1000 m), MODIS has proven effective for monitoring medium to large water bodies due to its consistent Red and NIR bands (Cao et al., 2022; Chen et al., 2025; Shi et al., 2022). These bands are sensitive to Chl-a absorption and scattering, minimizing interference from CDOM and TSS (Gitelson et al., 2011; Zhu et al., 2023).

We extracted Red (620–670 nm) and NIR (841–876 nm) reflectance values using Google Earth Engine and custom JavaScript for monthly median composites (Li et al., 2019). A multi-step QA/QC protocol was applied: MOD09Q1 QA flags masked clouds and aerosols (Hilker et al.,

2012), a land-water mask excluded shoreline pixels, and a 500 m buffer around sampling points ensured spatial accuracy (Bishop-Taylor et al., 2019). Additional filtering removed sun glint, striping, and outliers based on validated thresholds (Feng et al., 2018). Reflectance values were extracted in ArcGIS 10.8, and a linear regression model was developed to estimate Chl-a concentrations, leveraging the strong empirical relationship between MODIS bands and in-situ measurements (Song et al., 2013; Yang et al., 2017).

2.4. Retrieval Model of the Chl-a

A spectral index approach was employed to estimate Chl-a concentrations in lakes. Leveraging the bio-optical properties of Chl-a, various spectral indices, including band ratio, normalized difference, and single-band indices, were constructed (Table 1) (Wang et al., 2022). These indices, based on specific spectral band combinations, were designed to capture variations in Chl-a concentration. The optimal band combinations were identified by maximizing the Pearson correlation coefficient (r^2) between the calculated spectral indices and in situ Chl-a data. Subsequently, linear regression analysis was performed to establish a quantitative relationship between the selected MODIS bands and Chl-a concentrations. Finally, the derived linear regression models were applied to the MODIS imagery to generate Chl-a concentration maps for the lake.

Table 1: spectral indices for estimating Chl-a concentration.

Spectral indices	Calculation formula
Single Band index	$\text{Chl} - a = A + B * \rho_i$
Ratio Band index	$\text{Chl} - a = C + D * \frac{\rho_i}{\rho_j}$
Normalized difference index	$\text{Chl} - a = E + F * \frac{\rho_i - \rho_j}{\rho_i + \rho_j}$

where A, B, C, D, E and F are the correlation coefficients of the regression model, and ρ_i and ρ_j ($i, j = B1$ and $B2$) are the water reflectance of two bands selected by the MODIS data sources.

2.4.1. Chl-a Retrieval and Assessment Methods

To retrieve Chl-a concentrations, a linear regression model was developed using selected spectral features derived from MODIS-Terra data. Feature importance was assessed through Pearson correlation coefficients with in-situ Chl-a measurements. Between the tested variables, NIR reflectance shown the strongest

correlation ($R^2 = 0.53$), compared to NDVI ($R^2 = 0.46$), the Simple Ratio ($R^2 = 0.42$), and red reflectance ($R^2 = 0.23$). The results show that NIR reflectance is the best informative predictor of Chl-a concentration in Lake Tana. The Chl-a concentration was retrieved through linear fitting based on the MODIS surface reflectance data and in situ measured Chl-a concentration data. Additionally, the root-mean-square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) were used to evaluate the accuracy of the Chl-a retrieval results.

There is no fixed RMSE threshold for Chl-a remote sensing accuracy; tolerable values depend on trophic status, use, and data variability. In the mesotrophic to eutrophic lakes like Lake Tana, RMSEs of 2–10 $\mu\text{g/L}$ are mostly tolerable if they continue below 30% of the mean Chl-a concentration (Assegide et al., 2023; Makwinja et al., 2023; Shahvaran, 2024). This level of precision usually provisions consistent revealing of spatial and seasonal patterns. Conversely, further stringent precision (lower RMSE) may be essential for operational monitoring. The smaller the MAE value is, the closer the retrieval value is to the real value. The MAPE is the average absolute percentage error, where a MAPE value of 0% means a perfect model and a MAPE greater than 100% means an inferior model. The equations can be expressed according to (Cao et al., 2022).

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (Y_i - X_i)^2} \quad (1)$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |Y_i - X_i| \quad (2)$$

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^n \left| \frac{Y_i - X_i}{Y_i} \right| \times 100\% \quad (3)$$

where n represents the number of observed values, and X_i and Y_i represent the retrieval value and true value of the Chl-a, respectively.

2.4.2. Calibration and Validation of Regression Models

Following the methodology outlined by (Álvarez Robles, 2019), the predictive performance of the final regression model was evaluated using independent calibration and validation datasets. The dataset was randomly divided into two groups: 70% of the data was designated for calibration, to develop the linear regression model. The remaining 30% of the data served as the validation dataset, used to assess the accuracy of the regression coefficients derived from the calibration process.

2.5 Statistical Methods

To assess long-term trends in Chl-a concentration, the non-parametric Mann–Kendall test (Kendall, 1948; Mann, 1945) was applied to MODIS-derived time series data from 2008 to 2018 for August, December, and March. This test evaluates whether a monotonic upward or downward trend exists by comparing the sign of differences between pairs of observations. The normalized test statistic (Z) indicates trend direction and strength: $Z > 0$ suggests an increasing trend, $Z < 0$ a decreasing one. At a significance level of $\alpha = 0.05$, trends are considered statistically significant when $Z \geq 1.96$ (Douglas et al., 2000). Results confirmed significant seasonal trends in Chl-a, supporting the reliability of satellite-based monitoring.

3. Results

3.1 Observed Chl-a Concentrations

The Chl-a concentration was measured at 143 sampling locations across Lake Tana. The average Chl-a concentration increased markedly from 2.2 µg/L (ranging from 0.1 to 19.4 µg/L) in August 2016, to 13.6 µg/L (ranging from 0.1 to 148.2 µg/L) in December 2016, and reached a peak of 21.4 µg/L (ranged from 0.1 to 191.6 µg/L) in March 2017 (Table 2 and Table S1 in the supplemental material). Both the mean and the range of Chl-a values show a distinct seasonal progression, with the lowest concentrations occurring during the rainy season (August) and the highest concentrations during the dry season (March).

Spatially, Chl-a concentrations in August exhibited two distinct zones, with minimum values in the western side and maximum values in the eastern side of Lake Tana (Figure 2a). In December, the highest concentrations appeared in the southeastern and northeastern regions, while the western part still had the lowest concentrations (Figure 2b). The lowest concentration in December extended to the majority of the northern part and limited areas in the east. Conversely, during the dry season in March, the spatial distribution changed completely, with the lowest concentrations in the south, northeast, northwest, and certain parts of the central lake, and the maximum concentrations in the north, east at the entrance of the Gumara River, and southwest at the entrance of the Gilgel Abay River (Figure 2c).

Table 2: Descriptive statistics for the measured Chl-a concentrations of Lake Tana in µg/L

Aug 2016, Chl-a (µg/L)	Dec 2016, Chl-a (µg/L)	Mar 2017, Chl-a (µg/L)	
Mean	2.2	13.6	21.4
Median	1.3	4.0	12.7
Standard Deviation	2.8	26.7	27.1
Range	19.3	148.1	191.5
Minimum	0.1	0.1	0.1
Maximum	19.4	148.2	191.6
Confidence Level (95%)	0.5	4.4	4.5

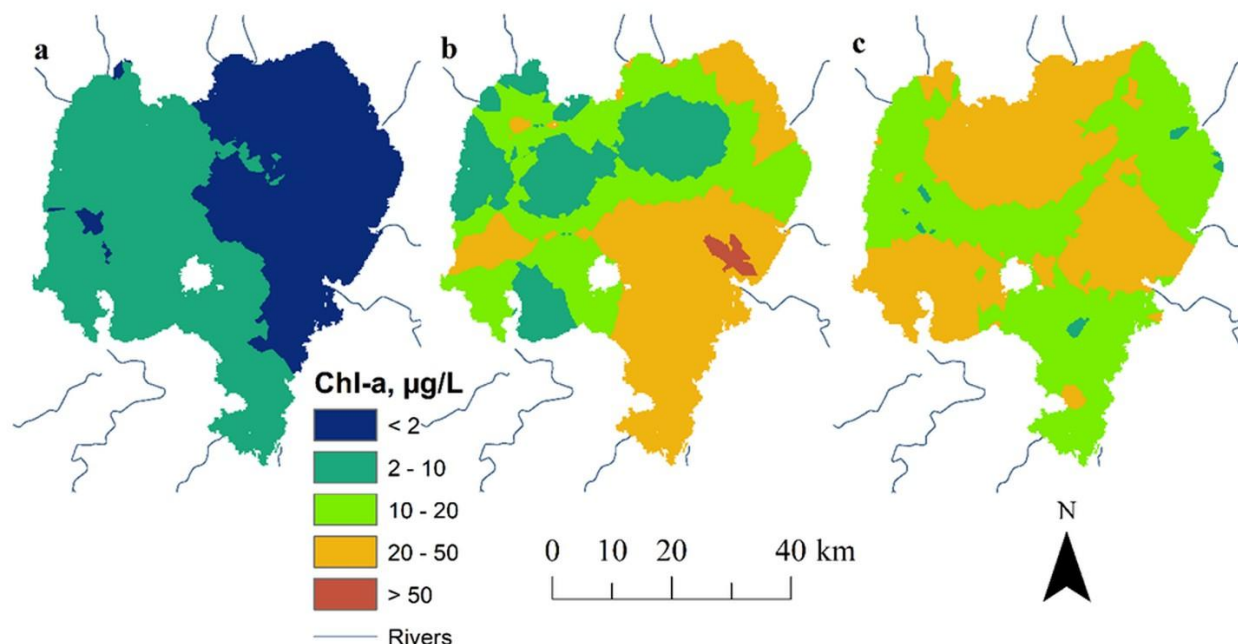


Fig. 2: Measured Chl-a concentrations in $\mu\text{g/L}$ of Lake Tana on: (a) August 2016; (b) December 2016, and (c) March 2017

3.2 Correlation between estimated and measured Chl-a concentrations

Predicted Chl-a concentrations exhibited a clear seasonal trend, increasing substantial from August to March in alignment with the observed data. Specifically, predicted Chl-a values followed a parallel trajectory, starting at 2.86 $\mu\text{g/L}$ in August, progressing to 15.35 $\mu\text{g/L}$ in December, and reaching a maximum of 21.75 $\mu\text{g/L}$ in March, as detailed in Tables 2, 3 and Table S2 in the supplemental material. This upward trend indicates a maximum concentration during the dry season, suggesting a strong influence of seasonal factors on algal growth. The prediction accuracy evaluated with RMSE and MAE was within a reasonable range (Table 3).

Table 3: Descriptive statistics for the measured versus estimated Chl-a concentrations in $\mu\text{g/L}$.

Date	Mean measured Chl- a ($\mu\text{g/L}$)	Mean estimated Chl-a ($\mu\text{g/L}$)	Max	Min	SD	RMSE	MAE	MAPE
22-31 Aug-2016	2.2	2.86	6.85	0.0	1.87	2.76	0.42	12.50%
14-22 Dec-2016	13.6	15.34	157.40	0.0	26.11	5.89	0.90	3.13%
14-23 Mar-2017	21.4	21.75	58.16	0.0	12.03	8.04	1.23	6.80%

A consistent linear relationship was identified between Chl-a concentrations and various combinations of red and near-infrared (NIR) bands derived from MODIS-Terra reflectance data. Notably, the NIR band exhibited the highest correlation, proving most effective for Chl-a retrieval across all sampling periods. Consequently, specific regression equations were developed for each sampling period. For August, the calibrated relationship between Chl-a and MODIS-Terra reflectance is represented by equation (4), visually depicted in Figure 2. Similarly, equations (5) and (6) detail the calibrated regression relationships for December and March, respectively.

$$Chl - a = -38.75 * \rho NIR + 8.18, \text{ for } r^2 = 0.53, n = 100 \text{ and } p < 0.001 \quad (4)$$

$$Chl - a = 1001.7 * \rho NIR - 13.19, \text{ for } r^2 = 0.56, n = 100, \text{ and } p < 0.001 \quad (5)$$

$$Chl - a = -606.3 * \rho NIR + 68.56, \text{ for } r^2 = 0.61, n = 100, \text{ and } p < 0.001 \quad (6)$$

where Chl-a is expressed in $\mu\text{g/L}$, n is the number of samples, p indicates a statistically significant probability of the linear relationship ($p < 0.001$), and r^2 represents the coefficient of determination, quantifying the goodness of fit for August (Table 3 and Figure 2), for December (Table S3 and Figure S1 in the supplemental material), and for March (Table S4 and Figure S2 in the supplemental material).

Table 3: Estimation statistics for various band combinations; bold numbers indicate the highest R^2 value in August 2016.

Band combinations*	R^2	Adjusted R^2	Standard error	Significance F
Red	0.23	0.22	0.96	0.0000
NIR	0.53	0.52	0.75	0.0000
Red+NIR	0.43	0.42	0.83	0.0000
Red-NIR	0.17	0.16	0.99	0.0000
NIR/Red	0.42	0.41	0.83	0.0000
NDVI (red-NIR/red+NIR)	0.46	0.46	0.8	0.0000

*The band explaining the best relationship with the Chl-a has the highest R^2 and lowest standard error, which is indicated in bold.

The correlation analysis confirmed a significant relationship between MODIS near-infrared (NIR) band reflectance and Chl-a concentration, though the strength of this correlation varied across different months, as evidenced by the fluctuating r^2 values in equations (4-6). Notably, the r^2 values demonstrated that the MODIS NIR band effectively predicts Chl-a concentrations. Furthermore, equations (5) and (6) provide the model coefficients necessary to calculate Chl-a levels across the entire surface of Lake Tana, utilizing the pixel reflectance values from the satellite imagery. The statistical significance of these correlations was confirmed by p-values consistently below 0.05 ($P < 0.05$).

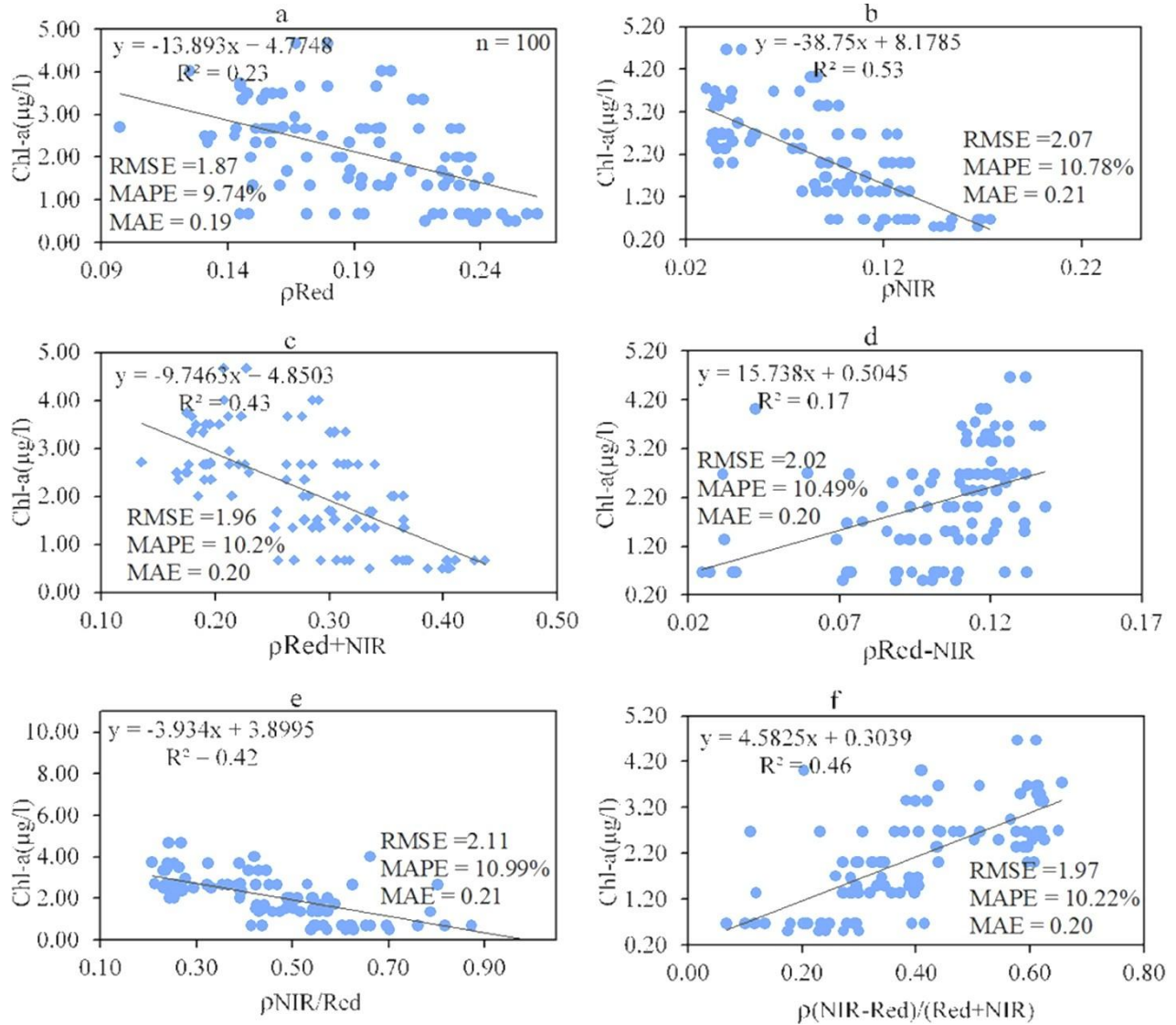


Fig. 3: Scatter plot of observed Chl-a (µg/L) against Mod 09 Q1 surface reflectance bands in August 2016.

Figure 3 illustrates the relationship between MODIS spectral bands and Chl-a concentrations, revealing that the near-infrared (NIR) band as the most effective for Chl-a retrieval in Lake Tana.

The scatter plot in Figure 3 and supplementary Figures S1 & S2 show a clear linear relationship between NIR band reflectance and Chl-a levels, confirming its suitability for accurate estimation. In contrast, the red band showed minimal correlation, suggesting it is not informative for water quality retrieval in this context. This finding underscores the importance of the NIR band in MODIS for detecting Chl-a. Furthermore, the MODIS-derived Chl-a estimates exhibited a statistically significant correlation ($r^2 = 0.53$) with observed values, and a Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) at a p-value less than 0.005.

3.3. Predicted Ch-a distribution of Lake Tana

The predicted results revealed clear spatiotemporal variation in Chl-a concentration over Lake Tana across the observed months. The predicted Chl-a concentration averaged 2.86 µg/L in August 2016, with values ranging from 0 to 6.9 µg/L. In December 2016, the average increased to 15.35 µg/L, with values ranging

from 0 to 157.4 $\mu\text{g/L}$. Through March 2017, Chl-a reached an average of 21.75 $\mu\text{g/L}$, ranging from 0 to 58.6 $\mu\text{g/L}$ (Tables 3 & S2).

Figure 4 illustrates a consistent spatially increasing trend in Chl-a concentrations from August to March. In August, the lowest values were observed in the western part of Lake Tana, with higher concentrations in the east (Figure 4a). In December, the highest levels were recorded at the entrance of the main rivers (Figure 4b). In March, Chl-a concentrations were generally elevated throughout the lake.

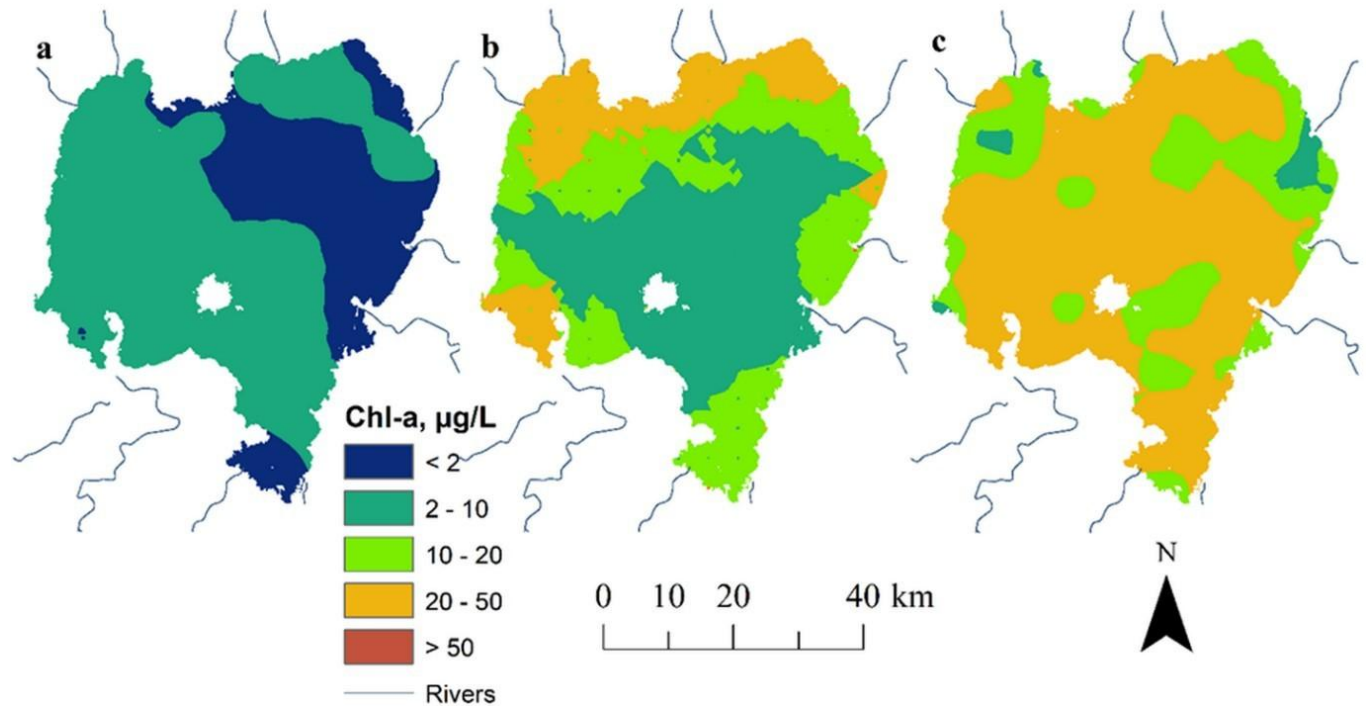


Fig. 4: Retrieval of the Chl-a concentrations in Lake Tana on: (a) August 2016; (b) December 2016 and (c) March 2017

3.4. Generating Chl-a Time Series Data for Lake Tana

Using the developed regression equations, the Chl-a concentrations were retrieved over a 10 year period (2008-2018). The spatial distribution of Chl-a concentrations was then mapped to visualize the spatial variations of each year for the predicted months (Figures S3, S4 and S5). Retrieved Chla concentration in the lake for August, December and March showed an increasing trend from the 2008 to 2018 periods (Figure 5). As the computed p-value is lower than the significance level alpha (0.05), the null hypothesis was rejected, and the alternative hypothesis was accepted in favor of the increasing trend in the series, particularly during the dry seasons.

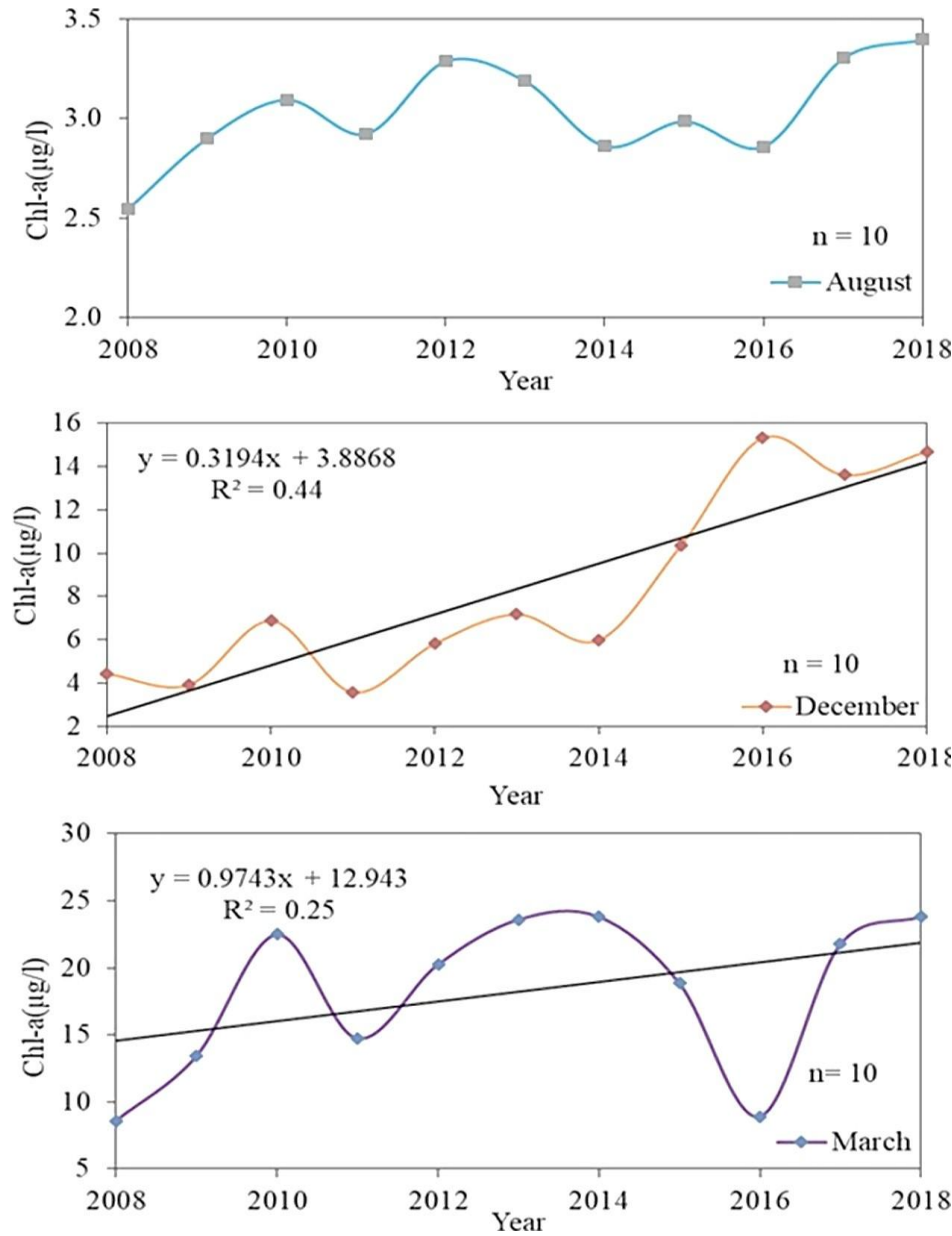


Fig. 5: Estimated Chl-a time series (2008–2018) for Lake Tana, derived from the developed models.

4. Discussion

4.1 Spatiotemporal Chl-a patterns

This study utilized MODIS/Terra Surface Reflectance 8-Day L3 data to estimate Chl-a concentrations in Lake Tana, which is seriously infested with water hyacinth. Chl-a concentrations resulting from satellite data were validated using in situ samples collected from 143 locations. A linear regression model applied to the red and near-infrared bands, with a spatial resolution of 250 m, achieved an R^2 of 0.53, RMSE of $2.76 \mu\text{g/L}$, MAE of $0.42 \mu\text{g/L}$, and MAPE of 12.5%. These metrics suggest that the model captures a significant portion of the spatial variability in Chl-a of the lake.

While the accuracy of MODIS-based models varied widely depending on the waterbody type, optical complexity, resolution of imagery, and choice of algorithm, the performance of this study aligns with findings in turbid large shallow lakes. For example, Gidudu et al.(2021) showed R^2 values of up to 0.80 and

RMSE around 5 $\mu\text{g/L}$ in Lake Victoria, the largest African lake, using empirical models with MODIS data, Oliveira Santos et al. (2024) indicated that MODIS 500 m products yield R^2 values between 0.6 and 0.75 for Chl-a in Brazilian reservoirs, with RMSE values from 2 to 4 $\mu\text{g/L}$, which is comparable with this study's results. In contrast, advanced performance was also noted in studies, for example, Feng et al. (2018) and Zhang et al. (2016) where R^2 exceeded 0.85 and RMSE was below 0.4 $\mu\text{g/L}$; However, these studies often targeted less turbid waterbodies.

The viability and accuracy of regression models for Chl-a estimation are often season-dependent, as the optical properties of water bodies vary throughout the year. For example, Kallio et al. (2001) confirmed that model coefficients derived for May differ noticeably from those for August, reflecting seasonal variations in water composition and light conditions. Similarly, Chl-a coefficients for August vary from those obtained in December and March (Figure 4). In Lake Tana, the spectral signal of Chl-a is weak in areas with high suspended materials, particularly during the rainy and post-rainy seasons (Ayele & Atlabachew, 2021). The Lake's surface extent and optical properties also fluctuate seasonally, influenced by rainfall and sediment load (Kebedew et al., 2021; Seong et al., 2017). Similar seasonal Chl-a variabilities have been observed in other African lakes, including Rift Valley lakes (Dagne et al., 2023) and Lake Naivasha (Ndungu et al., 2013). These results highlight the important of seasonal drivers in determining and controlling Chl-a dynamics.

The seasonal dynamics of Chl-a concentrations in Lake Tana are closely associated with climatic conditions, particularly during the dry season when increased sunshine hours and wind-induced resuspension of nutrients encourage higher rates of water hyacinth growth Kebedew et al. (2021). As underlined by Moges et al. (2017), Chl-a tends to increase during the dry period due to enhanced solar radiation. Our findings also revealed a consistent increase in Chl-a concentrations from August to March (Figure 5), a pattern commonly attributed to water hyacinth blooms encouraged by prolonged sunlight exposure. This seasonal blooming is further facilitated by the resuspension of particulate nutrients from the lake bed, mainly driven by wind-induced mixing, as noted by Kebedew et al. (2021).

Temporally, the Chl-a concentration predicted by the linear regression model for 2016 exhibited notable seasonal variability. The maximum predicted concentration reached 157.4 $\mu\text{g/L}$ in December, while the minimum was 0 $\mu\text{g/L}$ in August (Figure 4). This wide range of predicted values exceeded the observed in situ measurements (Table 2), showing that the model overestimated peak Chl-a levels by approximately 9.2 $\mu\text{g/L}$ in December, and underestimated lower extremes in August and March, where observed values were 0.05 $\mu\text{g/L}$ and 133 $\mu\text{g/L}$, respectively. These inconsistencies highlight the models' limitations in capturing nonlinear dynamics and extreme fluctuations commonly seen in complex inland waters (Gidudu et al., 2021). This pattern aligns with findings by Mucheye et al. (2022), who used Sentinel imagery to estimate Chl-a in Lake Tana and reported a maximum value of 40 $\mu\text{g/L}$ by the end of August, with a minimum of 4.4 $\mu\text{g/L}$ in June. Their study emphasizes that the peak Chl-a concentration tends to occur during the post-rainy season, rather than during peak rainfall months, likely due to nutrient influx from catchment runoff. Similarly, Wondie et al. (2007) observed that the highest spatial coverage of Chl-a also occurred after the rainy season, rather than during it, further emphasizing the delayed response of phytoplankton growth to nutrient input.

Comparatively, models using Landsat 7 ETM+ satellite data have also shown seasonal performance variability. Moges et al. (2017) found that the model underperformed during transitional months like November and May, with R^2 values of just 0.28 and 0.1, respectively. Regardless of these model performance issues, the average Chl-a concentration predicted by the MODIS based regression model in our study remained comparable to the in situ observed mean (Table 2), suggesting that while extreme values are poorly captured, the model is reasonably effective for estimating average concentrations. Despite that, recent literature further supports the need for seasonally adaptive or non-linear models to improve accuracy in predicting Chl-a in dynamic lakes (Deng et al., 2024; Zhang et al., 2024).

When comparing the Chl-a levels in Lake Tana with other African lakes, we found that Chl-a concentration measured from the two largest Ethiopian Rift Valley lakes in Ethiopia, Lake Abaya and Lake Chamo, between 2016 and 2019 ranged from $17.0 \pm 3.6 \mu\text{g/L}$ in Lake Abaya to $33.0 \pm 11.6 \mu\text{g/L}$ in Lake Chamo (Dagne et al., 2023) is lower with this study which ranges from 2.24 to 21.75 $\mu\text{g/L}$. A similar study in Victoria Lake using in situ Chl-a and MODIS satellite images showed poor performance ($R^2=0.03$) compared to our study ($R^2 = 0.53$) (Gidudu et al., 2021). In the case of Lake Malawi, Chl-a concentration estimations from MODIS surface reflectance were very low, ranging from 0.05 $\mu\text{g/L}$ to 0.27 $\mu\text{g/L}$, with a mean value was 1.0 $\mu\text{g/L}$, verifying that the lake was oligotrophic during this time (Chavula et al., 2009). In Lake Naivasha, Kenya, using MODIS surface reflectance, the maximum and minimum values of Chl-a concentration varied from 0 $\mu\text{g/L}$ in January to 40 $\mu\text{g/L}$ in December. According to Ndungu et al. (2013), MODIS satellite data tend to underestimate Chl-a concentrations compared to in-situ measurements. However, in this study, both under and overestimation occurred. Similar variability has been noted in other regions. For instance, Han and Jordan (2005) reported Chl-a concentrations ranging from 0.93 to 24.92 $\mu\text{g/L}$ in Pensacola Bay using Landsat ETM+, while Rani et al. (2019) found values between 3.22 and 3.41 $\mu\text{g/L}$ in Ghana's Densu River using Landsat-8. However, Chl-a concentrations in Lake Tana were higher than the above-stated lakes and rivers compared with the maximum value.

Overall, Lake Tana has undergone significant water quality degradation over the past two decades (Nerae et al., 2024b; Dersseh et al., 2022). Accurate predictions are essential for helping decisionmakers understand the extent of this decline. For instance, average spatial Chl-a concentrations have increased from 4.8 $\mu\text{g/L}$ in 2003 to 32.7 $\mu\text{g/L}$ in 2020 an eightfold rise (Wondie et al., 2007). Our findings confirm previous studies (Nerae et al., 2024) and Dersseh et al. (2022) showing a shift from slightly polluted to polluted conditions, driven by eutrophication, water hyacinth proliferation, nutrient enrichment, oxygen depletion, and elevated suspended solids (Kebedew et al., 2021). Given Lake Tana's role as the headwaters of the Blue Nile, this degradation poses downstream risks to the Upper Nile Basin (Kebedew et al., 2023; Worqlul et al., 2020). While this study does not exhaustively test all empirical models, the established relationship between remote sensing variables and Chl-a provides valuable insight into the drivers of water quality change.

4.2. Limitations and Recommendations

This study provides valuable insights into Chl-a dynamics and water hyacinth proliferation in Lake Tana; however, several limitations should be considered. The MODIS-based regression model showed reduced accuracy during transitional months and struggled to capture extreme Chl-a values, reflecting its limited sensitivity to seasonal variability (Gidudu et al., 2021; Moges et al., 2017). MODIS surface reflectance data may underestimate or overestimate Chl-a concentrations depending on water turbidity, cloud cover, and atmospheric conditions (Han & Jordan, 2005; Han et al., 2022; Ndungu et al., 2013). The use of a linear model may not fully capture nonlinear ecological responses, suggesting the need for seasonally adaptive or machine learning-based approaches (Zhang et al., 2024). Field sampling was constrained by logistical factors such as limited boat access, time, and budget, which may affect spatial representativeness (Moges et al., 2017; Worqlul et al., 2020). These limitations should be considered when applying the model to broader water quality assessments or management strategies. For future studies, using models that account for seasonal changes or applying machine learning approaches could improve predictions of Chl-a variability. Expanding field sampling and incorporating higher-resolution satellite data would also help capture the spatial and temporal patterns more accurately. In addition, managing the watershed through controlling nutrient runoff, restoring wetlands, and establishing buffer zones can reduce eutrophication and limit the spread of water hyacinth. Together, these steps would provide a clearer understanding of Chl-a dynamics and support effective water quality management in Lake Tana and similar freshwater systems.

5. Conclusion

Eutrophication, often signaled by elevated Chl-a levels due to excess nutrients, is challenging to assess in large lakes using traditional methods. Remote sensing offers a promising alternative solution. In this study, MODIS-Terra daily remotely sensed Chl-a concentrations were validated against 143 observed

measurements collected from a large shallow lake, Lake Tana, characterized by water hyacinth infestation. Results showed that the NIR band based on the MODIS image presented the best performance for estimating Chl-a in the lake. The variation of Chl-a concentration over the lake was associated with the seasonal variation of the regional climate. Chl-a concentration is greatest in the dry season and is lower in the rainy season. A strong statistical relationship was observed between Chl-a concentration and MODIS-Terra daily reflectance over Lake Tana. The linear regression model was used to estimate the Chl-a concentration time series for 10 years, and it was found that the highest concentration of Chl-a has an increasing trend, deteriorating the water quality of Lake Tana. The reasonable agreement between MODIS and in situ Chl-a data, together with favorable results from the linear regression model, reveals the applicability and necessity of further studies on estimating Chl-a, from satellite imagery in the area. The spatial patterns of Chl-a concentrations in Lake Tana's coastal areas were higher than in the pelagic areas, likely due to higher nutrient and pollutant inputs from agricultural activities of the surrounding and upstream areas. Seasonally, the lowest concentration of Chl-a was observed in the rainy monsoon, associated with reduced wind waves, algal blooms, increased rainfall, diminished light, and higher dilution caused by new runoff. The highest levels of Chl-a were recorded during the dry monsoon period, when increased temperature, ample light, stagnant water, and biochemical changes promote phytoplankton growth. The research establishes a foundation for directly aiding researchers in their ongoing fight to eradicate water hyacinths from Lake Tana, Ethiopia, and other similar African lakes. Continued refinement of remote sensing models and incorporation of additional ecological variables will further enhance water quality monitoring and promote sustainable lake management practices. Furthermore, the study underscores the need for basin-wide management strategies that not only consider the ecological health of the lake but also actively coordinate with and support local initiatives, ensuring that community-level practices align with broader conservation and water quality goals.

Author Contributions

B.W.A. contributed to conceptualization, data collection and analysis, writing the first draft, and incorporating feedback from co-authors. F.A.Z. contributed to research objectives, and methodologies, and provided overall supervision of the research work. M.G.K. helped in reviewing, structuring the paper, and rewriting the initial draft. S.T. and M.D.N. provided valuable feedback through manuscript restructuring, review and editing. All the authors declare that they reviewed the manuscript and accepted the published paper.

Data availability statement

The data used for the research are available from the first author upon request (bekalu_weretaw @ dmu . edu . et).

Conflicts of interest

The authors have declared no conflict of interest.

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