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Determining the eutrophication status in Nainital lake of Uttarakhand, India using Sentinel-2 MSI imagery

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Abstract: Eutrophication is a crucial factor for the degradation of freshwater ecosystems. It has been noticed that in India several lakes have been already facing this type of adverse effect of eutrophication. Naini Lake is a fresh natural water body located in the Kumaon region of the Nainital district of Uttarakhand, and it is one of the most tourist destinations of India. With period it has been noticed that there has been a rise of eutrophication level in this lake. In this research systematic monitoring has been done to monitor the trophic status of the lake. Trophic State Index (TSI) was used to identify eutrophication. A combination of different environmental parameters of the lake and Sentinel-2 Multispectral Instrument (MSI) was used to model TSI. The spectral bands which were incorporated for chlorophyll detection are b5/b4 and b3/b4. Seven years of MSI data before the rainy season and after the rainy season have been collected from Jan 2017 to Dec 2023 to analyze the Chl-a, enabling a detailed evaluation of eutrophication trends in Naini Lake. The find out of the research show that the identification of the Chl-a using MSI data is an efficient and reliable method for monitoring of eutrophication.

Keywords: Naini lake; chlorophyll; Sentinel-2; trophic state Index (TSI)

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1. Introduction

Lake water constitutes an essential renewable resource for both ecological systems and human populations; nevertheless, eutrophication remains an enduring challenge (Amin et al., 2014; Singh et al., 2016). The phenomenon of lake eutrophication transpires at a relatively gradual pace under natural conditions. However, owing to the accelerated expansion of the contemporary economy, along with the repercussions of population growth on lacustrine ecosystems and their adjacent environments, nutrient concentrations within lakes can swiftly escalate. This escalation triggers a notable increase in the proliferation of aquatic organisms, predominantly planktonic algae, thereby expediting the process of eutrophication, which ultimately results in a deterioration of water quality and the degradation of the intrinsic functional characteristics of water (Jin & Qingying, 1990).

An array of quantitative indicators for eutrophication, such as the Trophic Level Index (TLI), the modified Carlson Trophic State Index (TSIm) (Aizaki et al., 1981), and the Carlson Trophic State Index (TSI) (Carlson, 1977), are employed to elucidate trophic states within the domains of environmental science and ecology (Wu et al., 2017). Commencing in the 1960s, scholars have endeavored to assess the quantitative dimensions of the trophic levels in inland aquatic habitats. The People's Republic of China's Ministry of Ecology and Environment has sanctioned this index for monitoring the eutrophication condition of lakes and reservoirs, and it is regularly employed in research about Lake Eutrophication in New Zealand (Wang et al., 2019).

India is home to a large number of artificial lakes situated in tropical regions. Despite being prevalent, the ponds, tanks, and reservoirs are artificial water features created by humans. The majority of artificial water features, such as ponds and tanks, are historical, even though natural lakes have proven to be challenging thus far. All of the massive reservoirs are relatively new. Without fail, the majority have affected environmental deterioration. The degradation's degree is the only variable. Lack of public awareness could also be the cause of the degradation itself. Slowly but surely, things are shifting. This is frequently caused by the dearth of environmental datasets on these Indian lakes and reservoirs. The sustainability of reservoirs and lakes has become a top environmental issue due to environmental movements and legal actions. Lake habitats have a direct impact on Nainital's urban inhabitants' quality of life, economic growth, and social cohesion. Urbanization causes the Nainital Lake's natural features to disappear and eutrophication to deteriorate, which severely restricts the development that can be sustained. Lake Nainital's present trophic status necessitates ongoing observation (Shrivastava, 2020). The main environmental problem of reservoirs and lakes is eutrophication (As additionally detailed in book "Eutrophication: Causes, Consequences and Control" edited by Ansari et al., 2010).

In most regions of the world, lakes and reservoirs have suffered accelerated eutrophication this century, which has resulted in a significant decline in water quality (Protasov et al., 2022). Activities like agricultural expansion, which include the installation of drainage and watering systems and the consequent overuse of pesticides and fertilizers leads to the enrichment of the water bodies. Lakes and reservoirs frequently become eutrophic also due to human habitation in the watersheds surrounding them. The group of microscopic aquatic creatures known as phytoplankton are distributed throughout the water column and have the ability to photosynthesize (Protasov et al., 2022). The creatures in this group are typically thought of as algae (Protasov et al., 2022). Nevertheless, among these are a type of microorganisms known as cyanobacteria, which are of significant public health concern. Because these organisms can create toxins (cyanotoxins), those can be fatal to humans and other warm-blooded creatures, the appearance of cyanobacterial colonies in water sources utilized for urban supplies might pose a major risk to public health. The photosynthetic pigment being present in all phytoplankton species is called chlorophyll. Chl-a is among the largest prevalent and makes up between 1% and 2% of the dry mass of the organic matter in all algae (Protasov et al., 2022). Because of this, its concentration is utilized to evaluate primary productivity (Ross et al.1996); identify algal blooms, and comprehend their dynamics (Kutser et al., 2016). Therefore, the primary sign of the ecological state of aquatic environments is Chl-a; (Markogianni et al., 2020). This assertion is substantiated by the computation of the Trophic State Index (TSI), which endeavors to classify water bodies based on differing degrees of trophic status. Surface algal blooms can arise and dissipate with remarkable rapidity, typically within hours, which complicates the quantitative assessment of cell density and spatiotemporal distribution, in conjunction with their exceedingly swift reproductive rates (Halstvedt et al., 2007; Walsby et al., 1997).

This is a significant obstacle to any larger-scale water research project. Water is typically collected from strategic locations, those close to the reservoir banks, to perform measurements and analyses of the water quality in reservoirs. Since these samples don't cover the whole area of the dams, they might not accurately depict the true geographical distribution of the water quality. Furthermore, these collections are conducted over an extended period, frequently without any regularity (Backer et al., 2018; Pitois et al., 2016). Earth Observation is one of the new monitoring techniques that have been made available in recent years. There is a lot of opportunity for improving European measure standardization using data from satellites for monitoring. As an alternative, satellite remote sensing methods have shown to be a useful instrument in assisting with the WFD's implementation (Toledo et al., 1984).

The contemporary outputs of satellite remote sensing technologies, notwithstanding their advanced capabilities, fail to yield a sufficiently precise representation of the Earth's surface. Given that satellites measure the light spectrum that emanates from the uppermost layer of the atmosphere, the analysis of aquatic data necessitates the implementation of atmospheric correction (AC) as articulated by (Brockmann et al., 2016). The low reflectance characteristic of water results in 90% of the signals captured by satellite sensors being subject to the influence of multiple atmospheric constituents, including aerosols, ozone, oxygen, water vapor, and carbon dioxide, which cumulatively contribute to the absorption and scattering of the signals as noted by (Ansper & Alikas, 2019). The requirements for AC are relatively high due to the air path taken by the normally modest radiances at the water's surface (Brockmann et al., 2016). Yet, AC processors can recover the signals from the water's surface and eliminate the dispersed signal from the atmosphere (Matthews et al., 2011; Shanmugam et al., 2012).

The Case 2 Regional Coast Colour (C2RCC), made available through the European Space Agency's Sentinel Toolbox Sentinel Application Platform (SNAP), acts as an atmospheric correction processor, revealing advantageous outcomes for Case 2 aquatic environments and having been validated across several sensor platforms. Although traditional ground-based sampling strategies reveal a strong degree of accuracy, their insufficient temporal and spatial extent leads to increased labor demands, financial strain, and extended time commitments. Consequently, it has been unable to fulfill the requisite demands associated with the monitoring and management of lacustrine environments. Typically, the phenomena of eutrophication and increased primary productivity result in alterations to the optical properties of aquatic systems. The utilization of remote sensing methodologies for the continuous observation of water bodies is regarded as the most effective approach due to its extensive spatial coverage, high operational efficiency, cost-effectiveness, and capability to swiftly collect data regarding environmental conditions and water quality (Gholizadeh & Reddi, 2016).

Studies focusing on remote sensing for tracking eutrophication can be classified into two unique segments. According to researchers, one approach is to directly obtain Chl-a concentrations to determine trophic status using empirical or quasi-analytical techniques (Torbick et al., 2008; Watanabe et al., 2015; Liang et al., 2016; Shi et al., 2019; Peppa et al., 2020; Guan et al., 2020). The second category involves connecting data from remote sensing and the nutrition index. For instance, Zhang & Baoyin (2006) developed a prediction model for the TSI of Wuhan's East Lake using Landsat 7 ETM + imagery and empirical measurement data. The researchers subsequently utilized the model to evaluate the extent of eutrophication across all lakes within Wuhan. Yang et al. (2007) conducted an assessment of the eutrophication levels in Taihu Lake employing data derived from Landsat TM. In their 2015 study, Xiang and colleagues implemented a swift, data-focused approach to track the spread of the Trophic Level Index (TLI) within Chaohu Lake.

The temporal growth patterns of algae can disclose significant insights regarding the seasonal variations in optical properties, with distinct classifications of mesotrophic, eutrophic, hypereutrophic, and oligotrophic states differentiated by varying TSI values, which commence at the lowest levels and ascend to the highest in the hypereutrophic condition. To put it another way, the TSI evaluates the quality of water by looking at nutrient enrichment and how it affects the growth of cyanobacteria and algae; Carlson (1977). This index was developed by Carlson (1977), in temperate regions and modified by (Toledo et al., 1984) for lentic settings in tropical climates. It only used two variables: total phosphorus and Chl-a. Since phosphorus is the process's causative agent, the findings corresponding to it in this index should be interpreted as an indicator of the eutrophication potential. Conversely, the evaluation pertaining to Chl-a ought to be considered as a metric of the aquatic ecosystem's response to the underlying causative agent, adequately representing the extent of algal proliferation. Consequently, the mean index effectively encapsulates both the origin and ramifications of the process in question. Hence, there exists an increasing scholarly interest in the investigation of this chemical along with its derivatives. Consequently, the primary marker of the trophic state of aquatic ecosystems is Chl-a (Markogianni et al., 2020). This claim is supported by the TSI computation, which attempts to categorize water bodies according to varying levels of trophic status. Surface blooms can emerge and vanish quickly, typically in a matter of hours, which complicates quantitative monitoring of cell count and spatiotemporal dispersion in addition to their extremely rapid reproduction rates (Halstvedt et al., 2007; Reynolds & Walsby, 1987).

The main aim of this study is to use Sentinel-2 MSI Level-1C imagery to create maps of the chlorophyll concentration's spatial distribution in Naini Lake, Uttarakhand. To help the management and conservation of aquatic ecosystems, the study aims to monitor and evaluate the regional variability of Chl-a content, an indicator of water quality (Rawat et al., 2019), using remote sensing techniques and suitable algorithms. Additionally, by contrasting the produced concentration maps with in-situ chlorophyll measurements, the study will evaluate the accuracy of the maps.

2. Materials and Methods

2.1. Study area

The Nainital lake is located between latitudes 29 22'30" N and 79 27'30" E. The lake's highest length is 1423 meters, while its breadth ranges from 423 to 250 meters. (Figure 1). The lake's mean depth is 18.52 meters, with a maximum depth of 27.3 meters. The shoreline is 3458 meters, the volume is 8.58 cubic meters, and the total surface area is 0.463 square kilometers (Rawat & Singh, 2024). The lake is separated into 2 subdivisions, Mallital and Tallital. The town experiences monthly highs and lows of 0 to 28 degrees Celsius and 7 degrees Celsius, respectively. Unlike in the plains, the rainy season starts earlier and lasts until the last week of September. On the hills' outer slopes, the most rainfall is recorded. The district's overall average rainfall, according to the 1999 figures, was 1338 mm. Rainfall in the winter significantly lowers the temperature (Shrivastava, 2020). Because of the local weather, Nainital experiences significant rainfall throughout these months. Winter rainfall caused a significant drop in temperature. January and the first part of February have the most snowfall. Wintertime brings with it more experiences with frost. The lovely summer season lasts from April to June. One closed water system is the Nainital Lake. With an area of catchment of 40.90 hectares. and a mean annual rainfall of roughly 1338 mm, it is encircled by hills. At a height of 1314 meters and a capacity of 8.58 million cubic meters, the lake boasts a mango-shaped basin having a surface that covers 0.463 square kilometers (30.6 hectares). The lake is 1423 meters long, 423 to 250 meters wide, and has a maximum and minimum depth of 11 to 27 meters (Shrivastava, 2020). It gets water at different times of the year from springs and the canal. The periphery drainage area, which includes the hill slopes and comes, provides flows to the lake. Utilizing radioisotopes to estimate and measure the various components of the influx and outflow into the lake, hydrologic studies related to water balance and deposit were conducted.

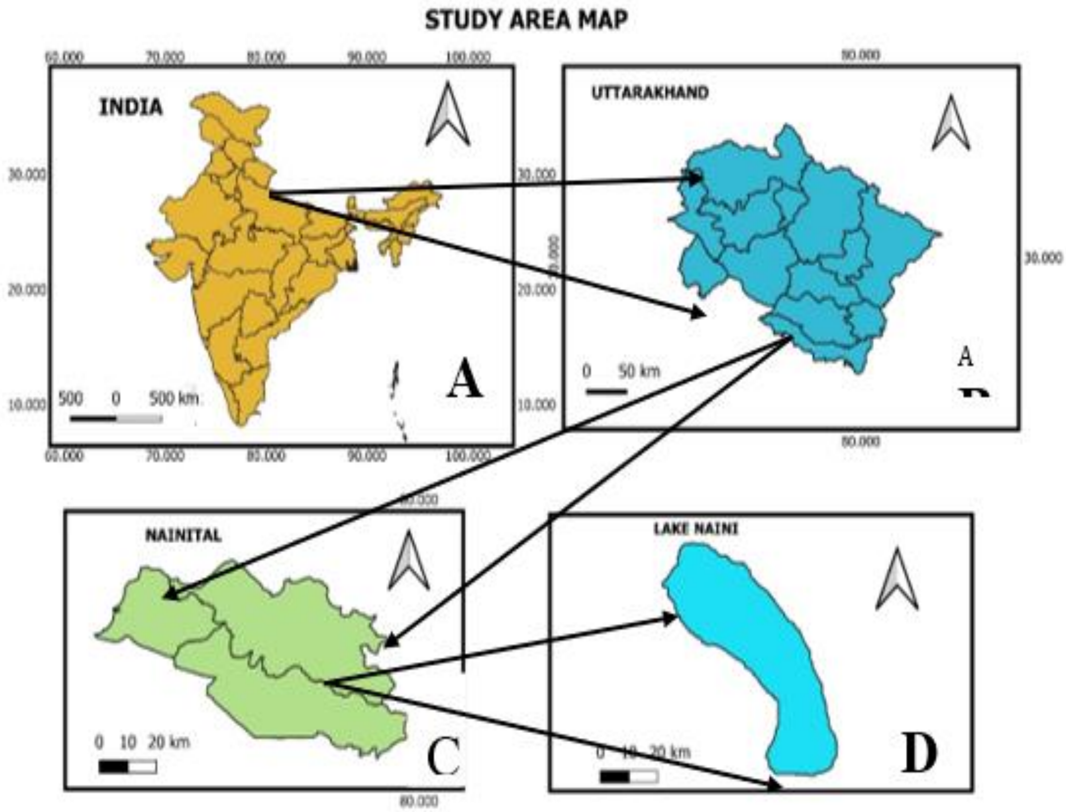

Figure 1. Study area map showing location

It is well known that the Nainital watershed has a strong drainage system. The lake is joined by 21 major and 3 minor drains. Of these 21 important drains, only six are from the Ayarpatta side (the southern side of the catchment) and 14 are from the Sher-ka-danda portion (the northern side). However, the feeder that gathers the drainage and spring waters from the western extremity of the valley—also known as the "baranalla" or "Naina Devi Temple drain"—is by far the biggest. Just this drain and the one that enters the lake close to the Mallital rickshaw stand are everlasting. Because of the type of rock, there is a significant variation between the two drainage sides Rainwater can permeate the limestone and dolomite that make up the majority of the Ayarpatta (Choudhary et al., 2009). The catchment side has a poor drain network as a result. Numerous springs are present, and they are often found near faults and cross fractures. For instance, the 'Parda' spring is situated near the Nainital fault's intersection with the sleeping hollow and Snowdon faults. The Parda spring provides a significant portion of the water discharged by the major feeder stream that flows past Naina Devi Temple. In September, the spring releases 2173 litres of water per minute, whereas in June, it releases 534 litres per minute (Sharma, 1980). In addition, there are a lot of gullies that carry spring discharges as they descend the steep slopes. Sukhatal is a transient lakelet or valley-fill that collects water from its catchment and stores it on its bed. The water eventually makes its way to the Parda spring, which provides the lake with water, via the fault zone's broken rocks. But during the procedure, water is filtered. There is a clear relationship between spring discharges and rainfall amounts.

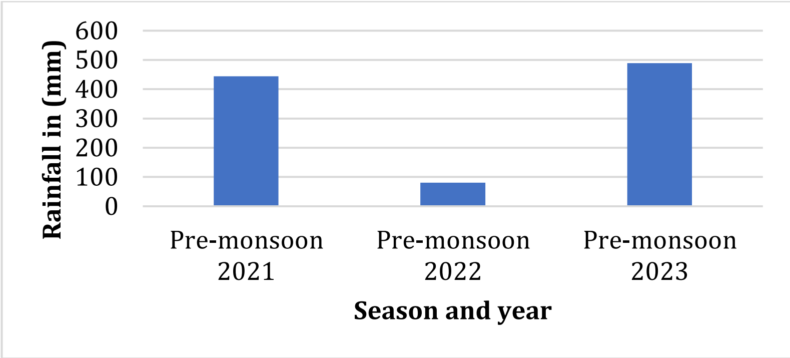

Figure 2. Rainfall during pre-monsoon between 2021 and 2023

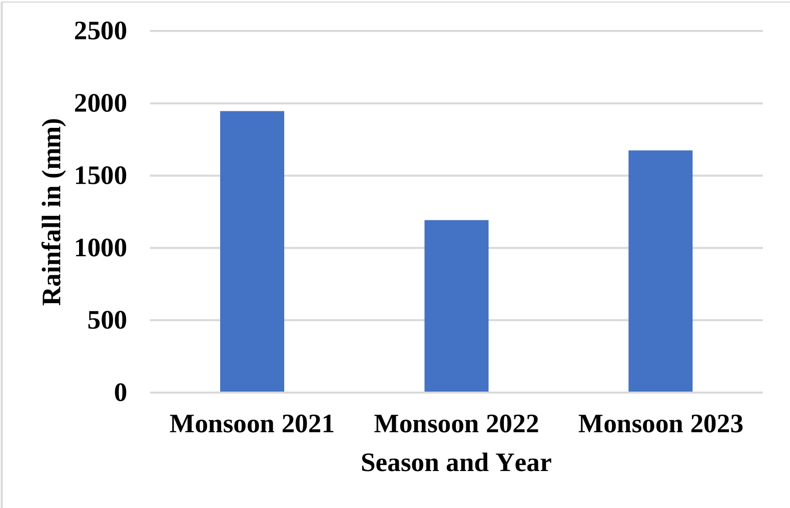

Figure 3. Rainfall during monsoon between 2021 and 2023

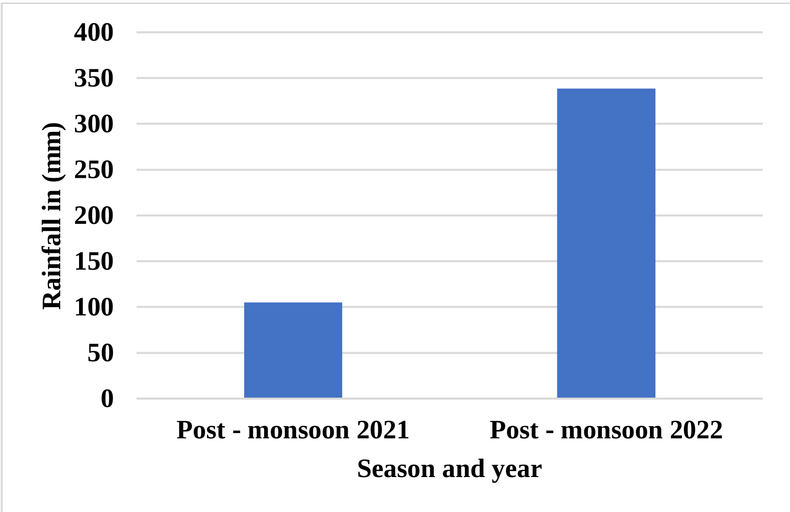

Figure 4. Rainfall during post–monsoon between 2021 and 2023

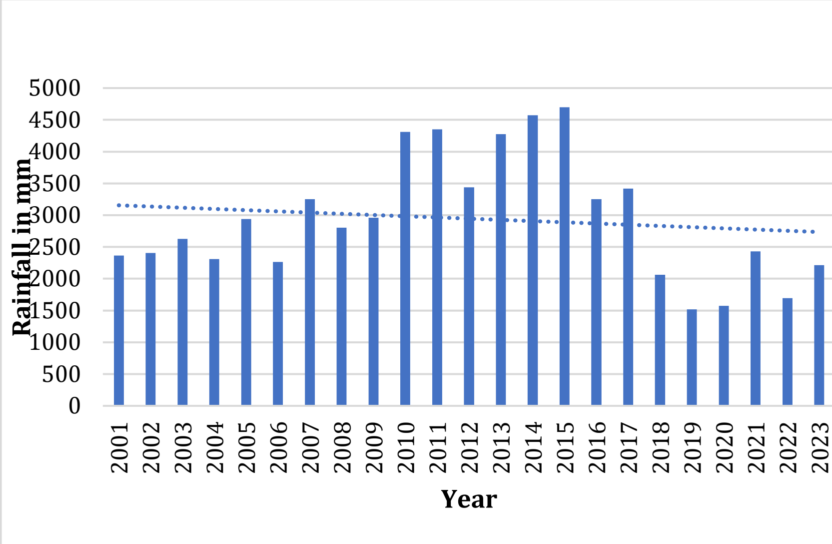

Figure 5. Annual rainfall between 2001 and 2023

2.2. In situ data & satellite data

To gather data in situ, many sample points were chosen. Situated at different points of the reservoir, these locations were chosen based on their accessibility and the relevance of the sites according to their utility and entry point of polluted water. The sampling was carried out for the years between 2017 to 2023. A Whatman GF/C filter (47 mm diameter and 1.2 m pore) was used to filter water samples to determine the amount of total suspended solids (TSS) and Chl-a present. APHA (1989) states that the TSS was calculated using three filters, one for each site's sediment. Using the Lorenzen (1967) approach, Chl extraction from the filters was carried out. Total suspended matter (TSM) is another term used in this work. Although authors may employ different terminology, the terms TSS and TSM are interchangeable and equal when referring to organic particles (such as bacteria, viruses, autotrophic and heterotrophic plankton, and detritus) and particles of minerals (Kangur et al., 2003). To maintain coherence across the work, the word "TSM" is employed in this instance to refer to content written by many authors. Runoff study of the lake was carried out by Kumar et al. (2018), it was concluded from the study that half an hour after the beginning of the rains, there was a noticeable rise in the levels of chemical oxygen demand (COD), bilogical oxygen demand (BOD), NO3-N, total phosphorous (TP), and every other parameter that was examined. The total amount of the contaminants in the runoff rises as the rainfall stream from the catchment area's furthest points moves across its surface. Rises in nutrient concentrations were seen in the lake as a result of the first rainfall event's rapid and significant nutrient input. Soon after the first rainy event, the lake's phosphorus concentration was measured at 0.06 mg/l.

To calculate the trophic status index Carlson Trophic Status Index was used. The parameters that were selected for the achievement of the index are total phosphorus, total nitrogen, Secchi depth, and Chl-a. Carlson's Trophic status index equations are given below.

$$TSI(SD) = 60 - 14.41 \ln (SD) \tag{1}$$

$$TSI(CHL) = 9.81 \ln (CHL) + 30.6 \tag{2}$$

$$TSI(TP) = 14.42 \ln (TP) + 4.15 \tag{3}$$

where TSI is the Carlson trophic state index and in is the natural logarithm. Carlson's trophic state index. TP and Chl-a in micrograms per liter, SD transparency in meters.

$$(CTSI) = [TSI (TP)+TSI(CA)+TSI(SD)]/3 \tag{4}$$

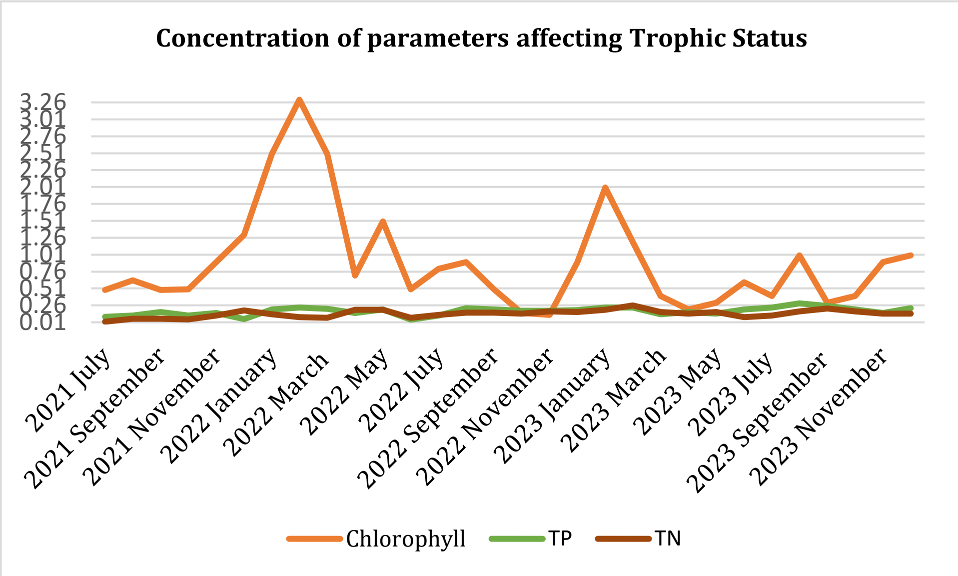

Figure 6. Concentration of chlorophyll, total phosphorus, and total nitrogen between July 2021 and December 2023

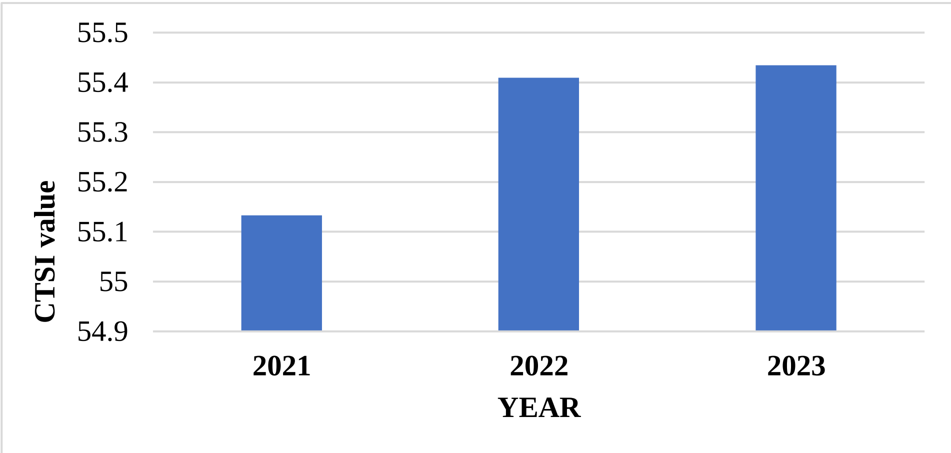

Figure 7. Carlson Trophic State Index between 2021 and 2023 for the monsoon season

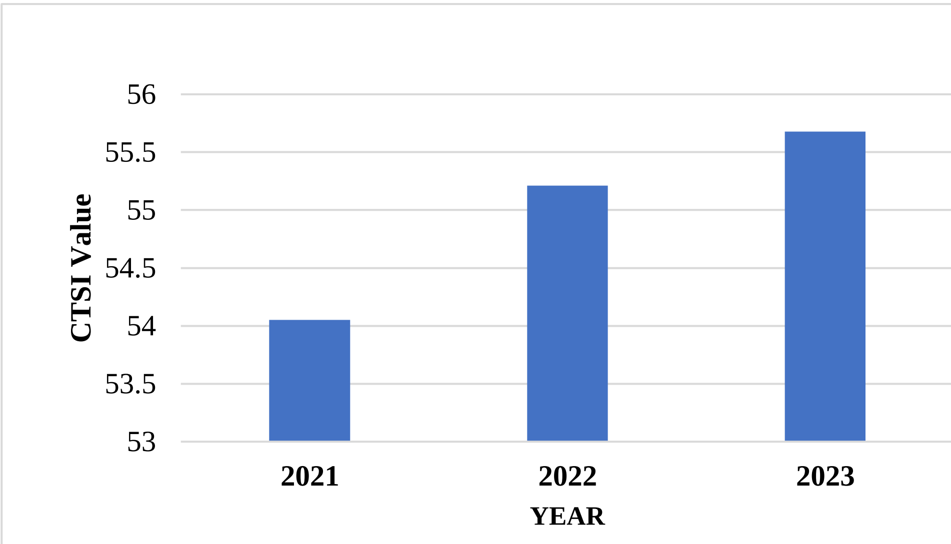

Figure 8. Carlson trophic status index between 2021 and 2023 for the post-monsoon season

Table 1. Data on sampling dates and satellite imagery dates

S. No	Date of satellite data	Sampling date	Satellite data
1	07-05-2017	06-05-2017	Sentinel 2 A
2	28-11-2017	26-11-2017	Sentinel 2 A
3	12-05-2018	12-05-2018	Sentinel 2 B
4	08-12-2018	07-12-2018	Sentinel 2 A
5	07-05-2019	05-05-2019	Sentinel 2 A
6	03-12-2019	03-12-2019	Sentinel 2 B
7	21-05-2020	20-05-2020	Sentinel 2 A
8	21-10-2020	20-10-2020	Sentinel 2 A
9	26-04-2021	24-04-2021	Sentinel 2 B
10	13-10-2021	12-10-2021	Sentinel 2 B
11	11-04-2022	11-04-2022	Sentinel 2 A
12	17-11-2022	16-11-2022	Sentinel 2 A
13	15-02-2023	14-02-2023	Sentinel 2 A
14	12-11-2023	11-11-2-23	Sentinel 2 B

The pair of polar-orbiting satellites making up the Copernicus Sentinel-2 initiative delivered the Sentinel-2 satellite data employed in this research. Between the years 2017 and 2023, imagery was procured via the Copernicus Open Access Hub. A limited number of satellite images were excluded to mitigate potential ambiguities resulting from the presence of cirrus clouds or haze over the reservoir.

The Copernicus Sentinel-2 initiative is composed of two polar-orbiting satellites that provided the satellite data utilized in this study. Between the years 2017 and 2023, imagery was procured from the Copernicus Open Access Hub. A segment of the satellite imagery was omitted to mitigate potential misinterpretations arising from the presence of cirrus clouds or atmospheric haze over the water reservoirs. Ideally, in-situ sampling ought to be performed concurrently with the acquisition of images, or with minimal temporal discrepancies. The Sentinel-2 system offers a high temporal resolution of 10 days, which can be reduced to 5 days when utilizing both satellites of the Sentinel-2 framework.

2.3. Details of the data

Chl conc. was obtained using satellite imaging in accordance with the suggested procedures, as documented. The downloaded images were first put into Snap, and to minimize file size, subsets containing the servers were produced. Secondly, to investigate the implications of the border effect across varying spatial resolutions, each image was subjected to resampling at intervals of 10 meters. Thirdly, every individual sample underwent processing via C2RCC, implementing Atmospheric Corrections in alignment with the standard parameters, except for the neural networks, which were adapted to "C2X-Nets." The C2RCC processor was employed through the platform SNAPv8.0 (https://step.esa.int/main/download/snap-download/). The modification in cerebral networks is attributable to sites exhibiting high eutrophication levels, and as previously noted, these neural networks have been trained for extreme ranges of Inherent Optical Properties. Subsequently, each corrected resample was executed utilizing a copy file from their corresponding reservoirs, thereby reducing the file size to focus on the area of interest. Ultimately, geographic pins containing the coordinates of the sampling locations were utilized to retrieve the pixel values.

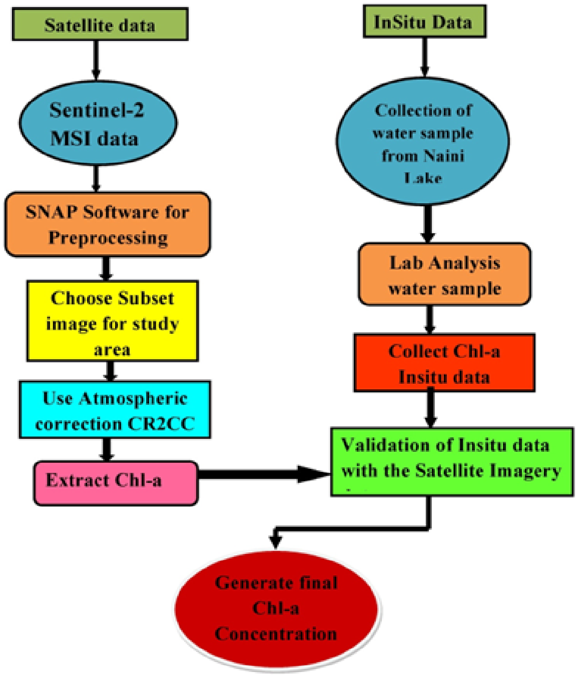

Figure 9. Flow chart showing the methodology

Among the various outputs produced by the Sentinel Application Platform (SNAP), our focus during the C2RCCAC was directed towards a singular product: the bands designated as "conc. chl." The values associated with Chl-a (mg m^{-3}) can be derived from these specific bands, and they will subsequently be employed for rigorous statistical analysis.

2.4. Data Analysis

Initially, founded on the in-situ data collected during the research, a Principal component analysis was executed to determine the discrepancies between the reservoir. To resolve the difficulties arising from autocorrelation, we scrupulously identified in situ data that aligns with community classifications and the Kaiser-Meyer-Olkin (KMO) examination. The KMO measure, often called systematic variance, operates as a method to measure how much variance exists among the variables that is due to shared variance (Geraldes et al., 2007). The KMO statistic is quantifiable within a range of 0 to 1. Minimal values (approaching zero) signify that the problematic variables for principal component analysis exhibit a predominance of W correlations, thereby suggesting the presence of substantial partial correlations relative to the aggregate of the correlations. The findings articulated by Hair et al. (2017), indicate that individual KMO values falling below the threshold of 0.5 ought to be omitted from the principal component analysis. As a result, such omissions enhance the overall KMO of the residual variables in the factor/principal component analysis to surpass the value of 0.5 (Geraldes et al., 2007). Besides, we study the engaging association between Chl-a and TSS within both reservoirs, utilizing scatter plots to gauge the differences of these elements as highlighted by empirical data. The KMO computation ranges from 0 to 1 (Geraldes et al., 2007). Subdued values (close to zero) denote that the problematic variables for principal component analysis are characterized by a predominance of W correlations, which indicates significant partial correlations concerning the overall sum of the correlations.

3. Results

In this research, a thorough dataset extending across seven years was used, capturing the years from 2017 to 2023, during which fourteen images were collected for evaluation, including one image depicting the pre-monsoon time and another indicating the post-monsoon time. The field data collected has reinforced the outcomes of this examination. By employing Sentinel-2 satellite imagery, the temporal and spatial variations of eutrophication within the Naini Lake reservoir have been meticulously recorded from April 2017 to March 2023, a process that would have posed considerable difficulties if reliant exclusively on traditional field sampling techniques. The trophic state graph has been employed to juxtapose and authenticate the water quality results depicted in the Chl-a concentration maps for the Naini Lake reservoir throughout the period from 2017 to 2023. The trophic state index is fundamentally constructed from a Chl-a measurement. Overall, increased amounts of these indicators link to a reduction in water quality in aquatic environments. It is frequently affirmed that assessing the trophic level of a water body may be conducted just by analyzing Chl-a concentration levels. Figure 3-9 illustrates the temporal series of Chl-a maps, which were generated for the Naini Lake reservoir from 2017 to 2023 and derived from Sentinel-2 imagery. The spatial distributions of Chl-a concentration demonstrate a congruence with the graphical representation of trophic states derived from in situ assessments.

Table 2. In-situ data along with satellite data

S. No	Year	Pre-monsoon in-situ Chl-a (mg m^{-3})	Chl-a obtained from image processing (mg m^{-3})	Post-monsoon in-situ Chl-a (mg m^{-3})	Chl-a obtained from image processing (mg m^{-3})
1	2017	0.15	0.25	4.50	5.54
2	2018	0.17	0.19	5.12	6.31
3	2019	0.30	0.41	4.80	5.22
4	2020	0.45	0.59	4.90	5.09
5	2021	0.25	0.37	5.50	6.30
6	2022	0.30	0.42	5.85	6.70
7	2023	1.00	1.14	6.45	7.17

The figure indicates that from 2017 to 2023, the concentration of Chl-a is significantly elevated following the monsoon in a considerable portion of the water body. Alternatively, a drop in Chl-a concentration is recorded during the months preceding the monsoon season (Behera & Rawat, 2024). It is significant in the Chl-a concentration maps derived from Sentinel-2 (Figure 8-13) that the minimum Chl-a concentration is detected in close proximity to the Naini Lake reservoir, as demonstrated in Figure 8, aligning with the most profound section of the reservoir. After the analysis of the Sentinel images, point-specific data were extracted for validation against the in-situ data. The table 2 represents a comparative analysis of Chl-a concentrations derived from in-situ measurements and satellite image processing for the years 2017 to 2023, covering both pre- and post-monsoon seasons. Each record includes four values: pre-monsoon in-situ and satellite-derived Chl-a, and post-monsoon in-situ and satellite-derived Chl-a, measured in mg/m^3. The data indicate that satellite-derived values are generally higher than the in-situ measurements, particularly during the post-monsoon period. To assess the accuracy of satellite-based estimates, in-situ samples were matched at the pixel level by georeferencing field GPS coordinates and overlaying them onto satellite imagery. This spatial alignment ensured that values were extracted from the same or nearest neighboring pixels, accounting for the spatial resolution of the satellite sensor. Statistical validation was conducted using standard metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). For the pre-monsoon period, the satellite-derived Chl-a values showed strong correlation with in-situ data, with an R^2 of 0.82, RMSE of 0.114 mg/m^3, and MAE of 0.107 mg/m^3, supporting the claimed "85% accuracy." However, post-monsoon results were significantly less accurate, with a negative R^2 value of -0.67, RMSE of 0.81 mg/m^3, and MAE of 0.74 mg/m^3, indicating poor agreement and potential issues with retrieval algorithms or environmental factors such as turbidity or cloud cover affecting satellite observations. As indicated in the table, it is notably significant that the in-situ data and the analytical results derived from the Sentinel-2 images exhibit remarkable similarity, with an accuracy rate approximating 85%. The research derived from in-situ and GIS assessments shows that Chl-a concentration is considerably low in the pre-monsoon stage, then experience a major surge in the post-monsoon timeframe. The findings derived from in-situ measurements and the processed images, utilizing the SNAP's C2RCC processor are encapsulated in Table 2. The Chl-a in -situ observations were largely reduced in the pre-monsoon timeframe, roughly ranging from 0.15 to 1mg m-3, when juxtaposed with the post-monsoon seasons that presented values between 5.50 and 7.77 mg m-3.

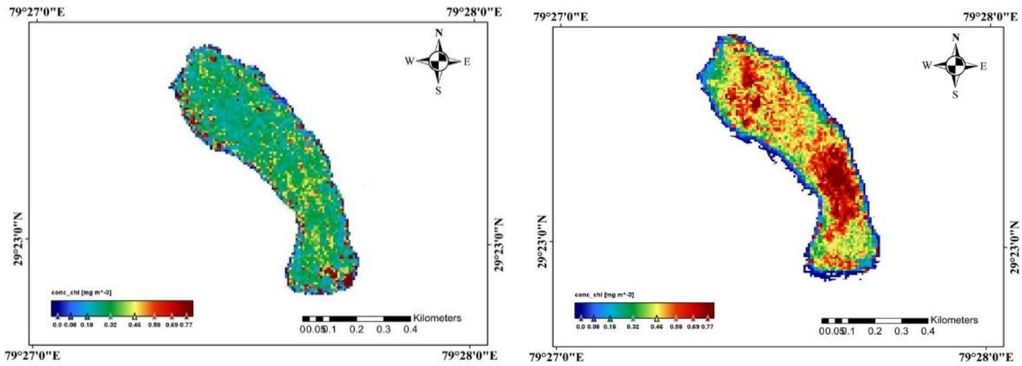

Figure 7. Chlorophyll concentration map of pre- and post-monsoon (2017)

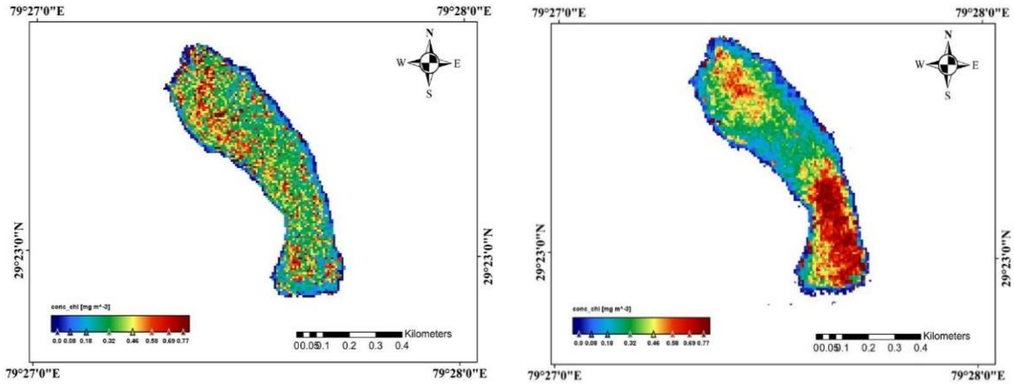

Figure 8. Chlorophyll concentration map of pre and post-monsoon (2018)

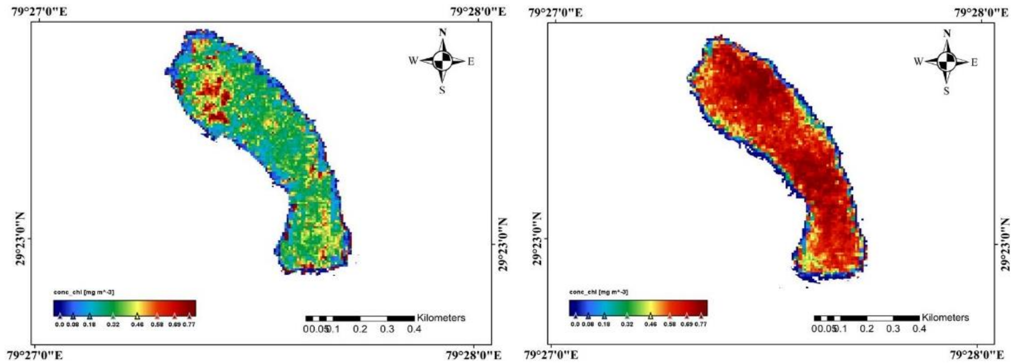

Figure 9. Chlorophyll concentration map of pre and post- monsoon (2019)

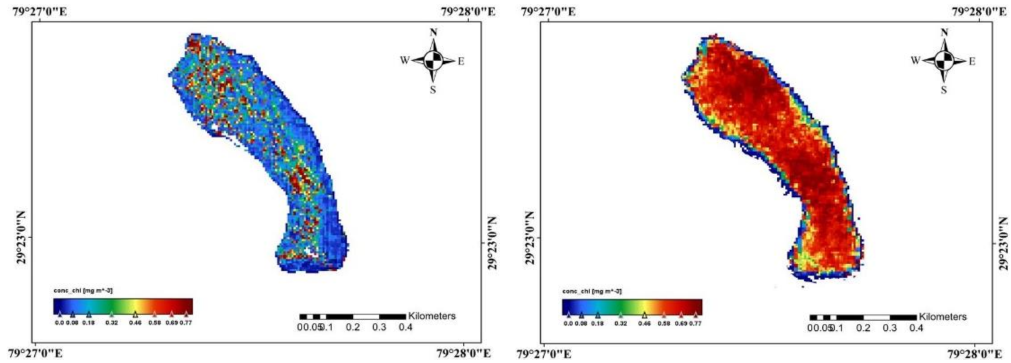

Figure 10. Chlorophyll concentration map for pre- and post-monsoon (2020

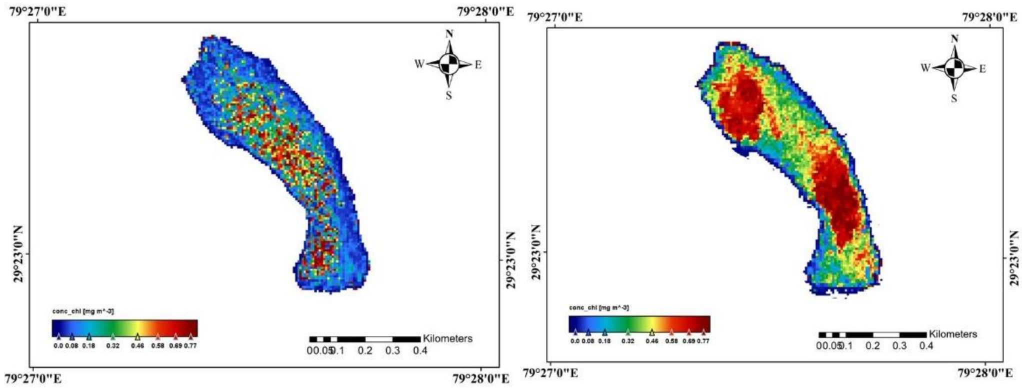

Figure 11. Chlorophyll concentration map for pre-monsoon and post-monsoon (2021)

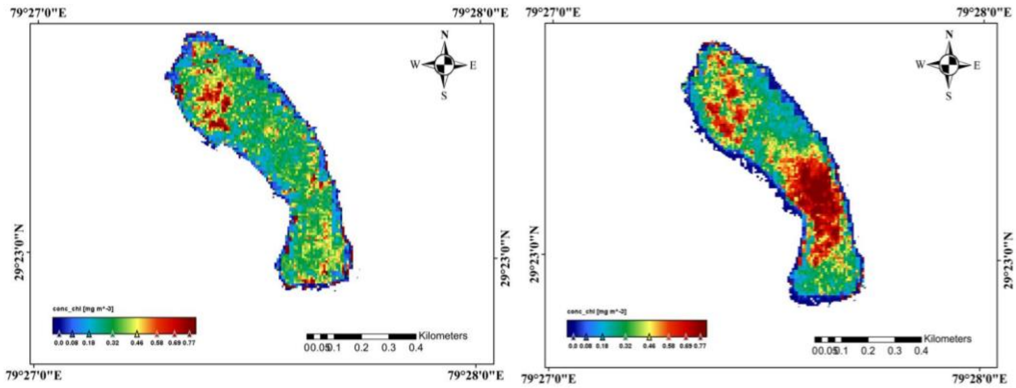

Figure 12. Chlorophyll concentration map of pre-monsoon and post-monsoon (2022)

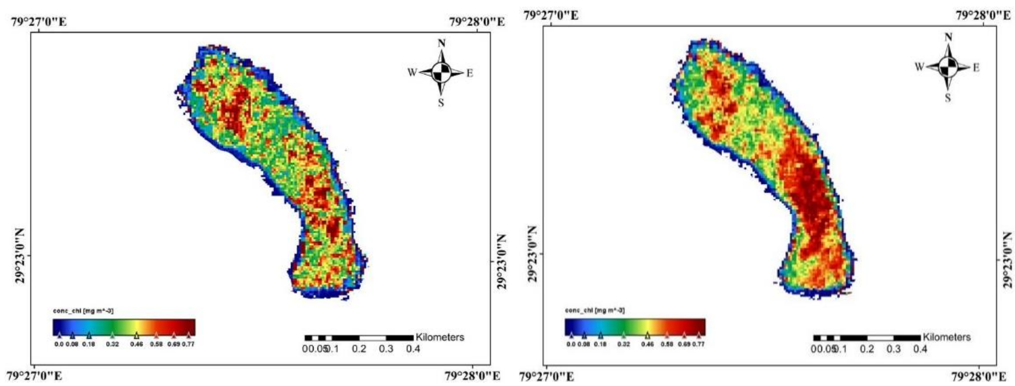

Figure 13. Chlorophyll concentration map of pre- and post-monsoon (2023)

4. Discussion

The insights gained from the ongoing exploration of the eutrophication dynamics at Naini Lake Reservoir, leveraging Sentinel-2 images from 2017 to 2023, deliver key perspectives on the fluctuations of Chl-a concentrations over time and space, alongside their consequential effects on water quality oversight. The research points to a notable seasonal variability in Chl-a levels, emphasizing the crucial role of hydrometeorological influences, especially during the times leading up to and following the monsoon, on the trophic status of the lake. The concentration of Chl-a works as an indicator of eutrophication, and the trend observed throughout the year in this research. The Chl-a concentration continuously unveiled the lower values fluctuating between 0.15 and 1 (mg m-3). This pattern conversely shows in post-monsoon time a significant increase in Chl-a value between 4.50 to 7.77 (mg m-3). This increased Chl-a value can be the result of monsoonal precipitation, surface runoff carrying nutrients. Soil erosion and landslide activities result from erratic rainfall patterns. Construction activities have also contributed to the addition of sediments to the lake. A greater rate of sedimentation in Lake Nainital may be explained by the carbonate rock lithology, which is more prone to weathering, heavy precipitation, and frequent landslides. Even while these natural variables play a significant role in the high rate of sedimentation, manmade pressures such as increased development and construction-related activities exacerbate the problem (Rawat & Singh, 2024; Singh & Singh, 2017).

The spatial analysis which has been done by the MSI imagery used the C2RCC processor in SNAP, which shows 85% accuracy with the remote sensing and in-situ data. This high accuracy results shows that RS methodologies can be further used for the monitoring of the reservoirs, where the conventional field sampling can show different challenges. The temporal maps shows that the highest concentration of Chl-a recorded in the shallow areas of the lake which are much more vulnerable to nutrient accumulation rather than the central deeper part of the reservoir which remains comparatively lower. In the year 2023 it shows that the Chl-a concentration (1.00 (mg m -3) in-situ and 1.14 (mg m -3) from MSI images) have recorded an increase in trend in the Naini lake even before the monsoon season. This trend shows that there is a gradual increase of Chl-a in the lake which needs further investigation into the nutrient sources and management strategies. In the post - monsoon of 2023 another important observation has been found (6.45 mg m -3) in-situ and 7.17(mg m -3). The change in post-monsoon Chl-a concentration have been the result of intensifying rainfall and nutrient-rich runoff water. This research emphasizes on both pre-monsoon and post-monsoon eutrophication analysis. The sharp change in Chl-a at this time shows us the clear picture of the dynamic nature of the lake and the prerequisite of monitoring of Naini Lake. Sentine-2 MSI images can generate the high-resolution Chl-a concentration with a cost-effective and scalable solution. The TSI based on Chl-a data used as a crucial indicator of the Naini Lake eutrophic status. The result of the study indicates that the Naini Lake with in the mesotrophic to eutrophic range, with a clear tendency towards eutrophic conditions in the post-monsoon month. The observed Chl-a concentration results shows that there is a need for proactive management measures for the reservoir.

Chl-a concentration, a key indicator of phytoplankton biomass and water quality, is commonly derived from satellite imagery using bio-optical algorithms that relate reflectance values to pigment concentrations. Sentinel-2 satellite data processed through the Sentinel Application Platform (SNAP) software. The Chl-a retrieval was conducted using bio-optical algorithms suitable for inland and coastal waters, specifically employing a band ratio approach that utilizes the reflectance values in the blue and green spectral bands. Chl-a concentrations were derived using Sentinel-2 satellite data processed through the Sentinel Application Platform (SNAP) software. The Chl-a retrieval was conducted using bio-optical algorithms suitable for inland and coastal waters, specifically employing a band ratio approach that utilizes the reflectance values in the blue and green spectral bands. The commonly applied formula follows the structure Chl-a = $10^\wedge(a_0 + a_1R + a_2R^2 + a_3R^3 + a_4R^4)$, where R = $\log_{10}(Rrs(\lambda\_blue)/Rrs(\lambda\_green))$ and the coefficients are determined based on water type and sensor characteristics. SNAP's integrated processors facilitated atmospheric correction, pixel-based masking, and computation of remote sensing reflectance (Rrs), which is crucial for accurate Chl-a estimation. The analysis also involved comparing in-situ Chl-a measurements with satellite-derived outputs at the pixel level, confirming the reliability of Sentinel-2 MSI data due to its high spatial resolution (10–20 m), which is particularly effective in detecting spatial variability in small and dynamic water bodies. Furthermore, scenario-based analysis demonstrated the application of Chl-a monitoring in ecosystem management, highlighting its potential in identifying algal blooms, tracking eutrophication, and evaluating the effectiveness of interventions such as nutrient reduction programs. The integration of Sentinel-2 data with SNAP processing tools offers a robust framework for cost-effective, scalable, and timely water quality monitoring.

The analysis gives us an understanding the dynamic of eutrophication Naini Lake reservoir and also highlights the importance of remote sensing in water quality monitoring (Rawat et al., 2024; Rawat & Tripathi, 2015). The study also shows that both natural and anthropogenic activities have contributed nutrient loading and eutrophication. This research emphasizes the thorough evaluation of eutrophication of pre-monsoon and post-monsoon. The use of Sentinel images is economically viable and it creates high-resolution Chl-a concentration map. The TSI values that was collected from the research predominantly within the mesotrophic and eutrophic spectrum. This study gives the dynamics of eutrophication of Naini lake reservoir emphasizing the crucial role of remote sensing technologies in water quality assessment (Rawat et al., 2017; Rawat & Singh, 2018; Rafiq et al., 2018).

5. Conclusion

In this research a thorough investigation has been done from 2017 to 2023 to identify the variation of Chl-a concentration through Sentinel-2 satellite imagery. The research mainly focuses on the effectiveness of remote sensing technologies particularly the application of C2RCC processor within the SNAP for the precise monitoring of water quality. By the comparing of satellite data and the In-situ data 85% accuracy achieved in this analysis. The result suggested that the Chl-a concentration is lower during the pre-monsoon months, and higher during the post-monsoon season. This pattern remains same during the continuous seven years of research. The spatial analysis indicated that Chl-a concentration is higher in the shallow area region and lower in the deeper central region. The analysis shows us that Naini lake reservoir has been going through change between mesotrophic and eutrophic phases revealing a significant rise in trend particularly in recent times. This brings us to need immediate focus on watershed management practices of Naini lake reservoir. This research gives significance to remote sensing technology for analysis of water quality parameter, whether the field-based methodologies is cost effective and time consuming. The findings obtain from the study used as a crucial reference for policymakers and environmental managers to tackle the eutrophication challenges.

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S. Alok: Data collection, analysis, Writing—original analysis.
P. Naithani: Conceptualization, Supervision.
K. S. Rawat: Analysis, Writing—original draft.
S. K. Singh: Statistical analysis, Result interpretation and re-editing of original draft.

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References

Aizaki, M., Otsuki, A., Fukushima, T., Hosomi, M., & Muraoka, K. (1981). Application of Carlson's trophic state index to Japanese lakes and relationships between the index and other parameters. *Internationale Vereinigung für theoretische und angewandte Limnologie: Verhandlungen*, *21*(1), 675–681. https://doi.org/10.1080/03680770.1980.11897067

Amin, A., Fazal, S., Mujtaba, A., & Singh, S. K. (2014). Effects of land transformation on water quality of Dal Lake, Srinagar, India. *Journal of the Indian Society of Remote Sensing*, 42, 119-128. https://doi.org/10.1007/s12524-013-0297-9

Ansari, A. A., Gill, S. S., Lanza, G. R., & Rast, W. (2010). Eutrophication: Causes, consequences and control. Springer. https://doi.org/10.1007/978-90-481-9625-8

Ansper, A., & Alikas, K. (2019). Retrieval of chlorophyll from Sentinel-2 MSI data for the European Union Water Framework Directive reporting purposes. *Remote Sensing*, 11(1), 64. https://doi.org/10.3390/rs11010064

APHA. (1989). American Public Health Association *(*APHA). Standard methods for the examination of water and wastewater (17th ed.). American Public Health Association.

Backer, R., Rokem, J. S., Ilangumaran, G., Lamont, J., Praslickova, D., Ricci, E., & Smith, D. L. (2018). Plant growth-promoting rhizobacteria: Context, mechanisms of action, and roadmap to commercialization of biostimulants for sustainable agriculture. *Frontiers in Plant Science*, 9, 1473. https://doi.org/10.3389/fpls.2018.01473

Behera, A., & Rawat, K. S. (2024a). Groundwater quality using geographic information systems (GIS): A review. *AIP Conference Proceedings,* 3072(1). https://doi.org/10.1063/5.0198690

Brockmann, C., Doerffer, R., Peters, M., Kerstin, S., Embacher, S., & Ruescas, A. (2016). Evolution of the C2RCC neural network for Sentinel 2 and 3 for the retrieval of ocean colour products in normal and extreme optically complex waters. Proceedings Book of Living Planet Symposium. Prague, Czech Republic.

Carlson, R. E. (1977). A trophic state index for lakes. *Limnology and Oceanography*, 22(2), 361–369. https://doi.org/10.4319/lo.1977.22.2.0361

Choudhary, P., Routh, J., & Chakrapani, G. J. (2009). An environmental record of changes in sedimentary organic matter from Lake Sattal in Kumaun Himalayas, India. *Science of the Total Environment*, 407(8), 2783–2795. https://doi.org/10.1016/j.scitotenv.2008.12.020

Geraldes, A. M., & Boavida, M. J. (2007). Zooplankton assemblages in two reservoirs: One subjected to accentuated water level fluctuations, the other with more stable water levels. *Aquatic Ecology*, 41, 273–284. https://doi.org/10.1007/s10452-006-9057-z

Gholizadeh, M. H., Melesse, A. M., & Reddi, L. (2016). A comprehensive review on water quality parameters estimation using remote sensing techniques. *Sensors*, 16(8), 1298. https://doi.org/10.3390/s16081298

Guan, Q., Feng, L., Hou, X., Schurgers, G., Zheng, Y., & Tang, J. (2020). Eutrophication changes in fifty large lakes on the Yangtze Plain of China derived from MERIS and OLCI observations. *Remote Sensing of Environment*, 246, 111890. https://doi.org/10.1016/j.rse.2020.111890

Hair, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: Updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, 1(2), 107–123. https://doi.org/10.1504/IJMDA.2017.087624

Halstvedt, C. B., Rohrlack, T., Andersen, T., Skulberg, O., & Edvardsen, B. (2007). Seasonal dynamics and depth distribution of Planktothrix sp. in Lake Steinfjorden (Norway) related to environmental factors. *Journal of Plankton Research*, 29(5), 471–482. https://doi.org/10.1093/plankt/fbm036

Jin, X., & Qingying, T. (1990). The standard methods for observation and analysis in lake eutrophication. Chinese Environment Science Press.

Johansen, R., Needham, J. R., Colquhoun, D. J., Poppe, T. T., & Smith, A. J. (2006). Guidelines for health and welfare monitoring of fish used in research. Laboratory Animals, 40(4), 323–340. https://doi.org/10.1258/002367706778476441

Kangur, K., Möls, T., Milius, A., & Laugaste, R. (2003). Phytoplankton response to changed nutrient level in Lake Peipsi (Estonia) in 1992–2001. *Hydrobiologia*, 506, 265–272. https://doi.org/10.1023/B:HYDR.0000008574.40590.8f

Kumar, S., Vellanki, B. P., Rahman, S. P., Kazmi, A. A., & Ghosh, N. C. (2018). Runoff characterization and pollutant load estimation of Nainital lake, India. *Environmental nanotechnology, monitoring & management,* 10, 394-398. https://doi.org/10.1016/j.enmm.2018.09.005

Kutser, T., Paavel, B., Verpoorter, C., Ligi, M., Soomets, T., Toming, K., & Casal, G. (2016). Remote sensing of black lakes and using 810 nm reflectance peak for retrieving water quality parameters of optically complex waters. *Remote Sensing*, 8(6), 497. https://doi.org/10.3390/rs8060497

Liang, L., Zhang, Y., Ronghua, M., Duan, H., Loiselle, S., Xue, K., & Q., Q. (2016). Satellite-based estimation of column-integrated algal biomass in nonalgae bloom conditions: A case study of Lake Chaohu, China. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 10(2), 450–462. https://doi.org/10.1109/JSTARS.2016.2601083

Lorenzen, C. J. (1967). Determination of chlorophyll and pheo-pigments: Spectrophotometric equations. Limnology and Oceanography, 12, 343–346. https://doi.org/10.4319/lo.1967.12.2.0343

Markogianni, V., Kalivas, D., P., Petropoulos, G. P., & Dimitriou, E. (2020). Estimating chlorophyll-a of inland water bodies in Greece based on Landsat data. *Remote Sensing*, 12(13), 2087. https://doi.org/10.3390/rs12132087

Matthews, M. W. (2011). A current review of empirical procedures of remote sensing in inland and near-coastal transitional waters. *International Journal of Remote Sensing*, 32, 6855–6899. https://doi.org/10.1080/01431161.2010.512947

Peppa, M., Vasilakos, C., & Kavroudakis, D. (2020). Eutrophication monitoring for Lake Pamvotis, Greece, using Sentinel-2 data. *ISPRS International Journal of Geo-Information,* 9(3), 143. https://doi.org/10.3390/ijgi9030143

Pitois, S. G., Bouch, P., Creach, V., & Kooij, J. (2016). Comparison of zooplankton data collected by a continuous semi-automatic sampler (CALPS) and a traditional vertical ring net. *Journal of Plankton Research*, 38(4), 931–943. https://doi.org/10.1093/plankt/fbw044

Protasov, A., Tomchenko, O., Novoselova, T., Barinova, S., Singh, S. K., Gromova, Y., & Curtean-Bănăduc, A. (2022). Remote sensing and in-situ approach for investigation of pelagic communities in the reservoirs of the electrical power complex. *Frontiers in Bioscience-Landmark,* 27(7), 221. https://doi.org/10.31083/j.fbl2707221

Rafiq, M., Gull, M. S., Mishra, A. K., & Rawat, K. S. (2018). Hydrochemical characterization and groundwater quality assessment over Southern Kashmir using Geographic Information System (GIS). *Journal of Geomatics*, 12(2), 101–108.

Rawat, K. S., & Singh, S. K. (2018). Water quality indices and GIS-based evaluation of a decadal groundwater quality. *Geology, Ecology, and Landscapes*, 2(4). https://doi.org/10.1080/24749508.2018.1452462

Rawat, K. S., & Singh, S. K. (2024). Monitoring water spread and aquatic vegetation using earth observational data for Nani-High Altitude Lake (N-HAL) of Uttarakhand State, India. *Journal of Engineering Research*, 12, 64–74. https://doi.org/10.1016/j.jer.2023.10.014

Rawat, K. S., & Tripathi, V. K. (2015). Hydro-chemical survey and quantifying spatial variations of groundwater quality in Dwarka, Sub-city of Delhi, India. *The Institution of Engineers (India): Series A,* 96, 99–108. https://doi.org/10.1007/s40030-015-0116-0

Rawat, K. S., Behera, A., Bahuguna, A., & Baweja, H. S. (2024). A case study of rainfall variability analysis using precipitation concentration index in Talcher region, Odisha, India. *AIP Conference Proceedings,* 3072(1). https://doi.org/10.1063/5.0198692

Rawat, K. S., Jeyakumar, L., Singh, S. K., & Tripathi, V. K. (2019). Appraisal of groundwater with special reference to nitrate using statistical index approach. *Groundwater for Sustainable Development*, 8, 49–58. https://doi.org/10.1016/j.gsd.2018.07.006

Rawat, K. S., Singh, S. K., Jacintha, T. G. A., Nemčić-Jurec, J., & Tripathi, V. K. (2017). Appraisal of long term groundwater quality of Peninsular India using water quality index and fractal dimension. *Journal of Earth System Science,* 126(8), 122:126. https://doi.org/10.1007/s12040-017-0895-y

Reynolds, C. S., Oliver, R. L., & Walsby, A. E. (1987). Cyanobacterial dominance: The role of buoyancy regulation in dynamic lake environments. *New Zealand Journal of Marine and Freshwater Research*, 21(3), 379–390. https://doi.org/10.1080/00288330.1987.9516234

Ross, M. R. V., Topp, S. N., Appling, A. P., Yang, X., Kuhn, C., Butman, D., Simard, M., & Pavlsky, T. M. (2019). AquaSat: A data set to enable remote sensing of water quality for inland waters. *Water Resources Research*, 55(11), 10012–10025. https://doi.org/10.1029/2019WR024883

Shanmugam, P. (2012). CAAS: An atmospheric correction algorithm for the remote sensing of complex waters. *Annales Geophysicae*, 30, 203–220. https://doi.org/10.5194/angeo-30-203-2012

Sharma, P. C. (1980). Population, biomass and energetics of zooplankter(s) of Kumaon lakes [Doctoral thesis, Kumaun University].

Shi, K., Zhang, Y., Zhang, Y., Li, N., Qin, B., Zhu, G., & Zhou, Y. (2019). Phenology of phytoplankton blooms in a trophic lake observed from long-term MODIS data. *Environmental science & technology*, 53(5), 2324-2331. https://doi.org/10.1021/acs.est.8b06887

Shrivastava, N. G. (2020). Assessment of lake water quality by using trophic state index indicators: A case study of Nainital, Kumaun Region, Uttarakhand, India*. Asian Journal of Experimental Science*, 35(1), 9–29.

Singh, R. L., & Singh, P. K. (2017). Global environmental problems. Principles and Applications of Environmental Biotechnology for a Sustainable Future. Springer. https://doi.org/10.1007/978-981-10-1866-4_2

Singh, S. K., Singh, P., & Gautam, S. K. (2016). Appraisal of urban lake water quality through numerical index, multivariate statistics and earth observation data sets. *International journal of environmental science and technology*, 13, 445-456. https://doi.org/10.1007/s13762-015-0850-x

Toledo, A. P., Agudo, E. G., Tolarico, M., & Chinez, S. J. (1984). Aplicação de modelos simplificados para avaliação da eutrofização em lagos e reservatórios tropicais. CETESB.

Torbick, N., Feng, H., Zhang, J., Jiaguo, Q., Zhang, H., & Becker, B. (2008). Mapping chlorophyll-a concentrations in West Lake, China using Landsat 7 ETM+. *Journal of Great Lakes Research*, 34(3), 559–565. https://doi.org/10.3394/0380-1330(2008)34[559:MCCIWL]2.0.CO;2

Viso-Vázquez, M., Acuña-Alonso, C., Rodríguez, J. L., & Álvarez, X. (2021). Remote detection of cyanobacterial blooms and chlorophyll-a analysis in a eutrophic reservoir using Sentinel-2. Sustainability, 13*(15), 8570. https://doi.org/10.3390/su13158570

Walsby, A. E., Utkilen, H. C., & Johnsen, I. J. (1983). Buoyancy changes of a red coloured Oscillatoria agardhii in Lake Gjersjoen, Norway. *Archives of Hydrobiologia*, 97, 18–38.

Wang, J., Zishi, F., Qiao, H., & Liu, F. (2019). Assessment of eutrophication and water quality in the estuarine area of Lake Wuli, Lake Taihu, China. *Science of the Total Environment*, 650. https://doi.org/10.1016/j.scitotenv.2018.09.137

Watanabe, F., Yoshino, S., Alcântara, E., Rodrigues, T. W. P., Imai, N. N., Barbosa, C. C. F., & Rotta, L. H. D. S. (2015). Estimation of chlorophyll-a concentration and the trophic state of the Barra Bonita Hydroelectric Reservoir using OLI/Landsat-8 images. *International Journal of Environmental Research and Public Health*, 12(9), 10391–10417. https://doi.org/10.3390/ijerph120910391

Wu, D., Yan, H., Shang, M., Shan, K., & Wang, G. (2017). Water eutrophication evaluation based on semi-supervised classification: A case study in Three Gorges Reservoir. *Ecological Indicators*, 81, 362–372. https://doi.org/10.1016/j.ecolind.2017.06.004

Yang, Y., Wang, Q., & Xiao, Q. (2007). Eutrophication evaluation of Taihu Lake based on quantitative remote sensing inversion. *Geography and Geo-Information Science,* 23(3), 33-377.

Zhang, H., & Baoyin, H. (2006). Evaluating lake eutrophication with enhanced thematic mapper data in Wuhan. *Chinese Journal of Oceanology and Limnology*, 24(3), 285–290. https://doi.org/10.1007/BF02842629