Assessment of Hydro-Chemical Properties of Rudrasagar Lake Ecosystem Using Comprehensive Pollution Index and Geoaccumulation Modelling: A Case from Ramsar Wetland of India

Abstract

Surface water quality assessment is crucial for sustainable ecosystem management as they are alarmingly susceptible to contamination. The recent study in the Rudrasagar Lake pioneered a novel approach combining geospatial techniques along with integrated environmental indices to demonstrate dynamics of spatial variation of contaminants. The fundamental objective of this study is to evaluate hydro-chemical properties of the water samples using inverse distance weighted method through comprehensive pollution index for wetland *(CPIW)* and Geoaccumulation index *(Igeo)*. To assess and determine the hydro-chemical characteristics and spatial variation, 24 sites from peripheral and core areas were selected for sampling. Variables were measured following the standard protocol and compared with WHO permissible limit. Meanwhile, bivariate and multivariate statistical approaches were employed to interpret the strong interdependence or magnitude among the variables. Principal component analysis (PCA) was utilised for data dimensionality reduction and source identification of the contamination. PCA revealed five factors accounted about 80.0% of the total variance in the surface water quality data set and attributed that anthropogenic and geo-genic factor responsible for spatial variations in physico-chemical parameters. CPIW varying from 0.46–1.50 and about 63.07% of the sampling sites indicated insignificant pollution, 26.92% indicated low pollution, while only 0.01% showed high pollution. Furthermore, Geoaccumulation index *(Igeo)* values suggested about 67.30% of sampling sites characterised by insignificant pollution zones, 32.69% fall under low pollution zones. CPIW indicates only 0.01% of the sampled sites fall under the highly contaminated zone. Additionally, spatial variation of each hydro-chemical property along with water quality clearly defined that anthropogenic and geo-genic factors mainly determined the sources of contamination. These findings signified substantial alterations in the water quality, which can offer valuable insights for targeted wetland management strategies and recommended that policy should be implemented immediately to manage and protect the overall wetland health.

Keywords: Hydrochemical dynamics, Water contamination, Spatial variation, Anthropogenic pressure

1. Introduction

Wetland has a multi-faceted role in providing enormous ecosystem services including sustaining biodiversity and ecological stability of the biosphere (Gupta et al., 2020). Wetland is considered as a sustainable reservoir of environmental services and contributes to carbon sequestration, regional climate modification, and livelihood improvement (Atiim et al., 2022; Xu et al., 2019). It is attributed as the primary source of water for agriculture, domestic use, fishing ground, and other recreation activities. Therefore, it is considered an integral component and dynamic biomes of the biosphere. It shows a decisive role in recharging groundwater including water purification (Kou et al., 2023; Zheng et al., 2023). Wetland water contamination has emerged as a critical concern affecting human health and socio-economic development and profoundly affecting the environmental landscape. Wetlands are mainly contaminated from sewage or wastewater disposal therefore nowadays water scarcity has become a prominent phenomenon adjacent to its catchment area (Chaudhuri 2022). The importance of preserving the wetland health cannot be overstated. Optimal wetland water quality fosters a healthy living environment and is intricately associated with human health, ecological balance and social well-being. Burgeoning urbanization, rapid industrialisation, modification in agricultural landscapes, and areal transformation in terms of regional development have created tremendous challenges to maintain water quality worldwide. Consequently, the impact of natural factors and anthropogenic activities accelerates alarming degradation in surface water quality. Deterioration of water quality directly impacts human welfare and sustainable future of the surface water sources and reservoirs.

Different international studies have attempted to examine the relative importance of wetland in maintaining biodiversity across different environmental gradients (Chen et al., 2023; Donde et al., 2023). Several studies have identified the value of wetlands in providing abundant resources and ensuring sustainable livelihood as well as aesthetic scenarios. Meanwhile, the necessity for wetland resources is rising exponentially owing to rapid population growth, urbanisation, and increasing demand in agricultural and industrial sectors (Faouzi et al., 2023; Lejri et al., 2022). Lim et al.(2012) determined that mine tailings, geological formations, mineral content in bedrock, aquifer minerals, and water-rock interactions governing mineralisation mechanisms like ion exchange, and mineral dissolution affect water quality. Multiple circumstances are controlling the discharge, transport and sequel of geo-genic components and ionic exchange from the mineralized rock to the water body (Salem et al., 2024; Nordstrom 2011). Therefore, wetlands are considered one of the most vulnerable zones globally, and act as repositories due to development activities (Dar et al., 2021). Various studies have been conducted to determine transformation and assess wetland health risk using fuzzy MCDM approaches and geoinformatics applications (Mondal et al., 2022). Another study by Eric et al. (2022) reported a significant decline in inland wetlands since the 20th century. Rising water scarcity is anticipated to cause a decline in water quality owing to droughts, floods, and dynamic nature of climate. This phenomenon potentially impacts the availability of water for drinking, agriculture and industrial purposes (du Plessis & du Plessis, 2017). Principal Component Analysis (PCA) ensures to identify the different groups of variables that are correlated with each other and thus can be considered as having a similar behaviour and common origin (He 2024; Kurita 2021). PCA is the most widely used quantitative approach for transforming an environmental monitoring dataset. It emphasised interrelated variables into a new set of variables. Principal components provide information on the most impactful parameters which describe the whole dataset while affording data complexity reduction with a minimum loss of original data (Chen et al., 2009;Serneels & Verdonck 2008).

Thus, water quality and quantity are intricately interconnected and determine accessibility and utilization of water resources (Mishra 2021). Water quality assessment relies on ambient physico-chemical and biological parameters (dos Santos 2021). Suitable and robust indices are essential in order to discern the ongoing trends of water quality (Uddin et al., 2024). The use of indices for assessing ecosystem health serves as a robust approach to communicate the state of an ecosystem to the general public and decision-makers. This will help in facilitating effective monitoring programs (Yadav et al., 2024). Indices provide benchmarks that assist in devising effective management strategies aimed at enhancing water quality (Alegre 2016). Therefore, a systematic and holistic study is crucial for sustainable wetland management which can significantly improve social and economic conditions of the dependent communities (Li et al., 2020). Simultaneously, water quality assessment is urgently demanded for strategic management and sustainable restoration of wetland resources. Monitoring and assessing wetland water quality at a certain interval requires special attention, particularly when the wetland serves as a drinking water source and is threatened by multiple human actions within the catchment that may result in contamination. Previous studies have been carried out on iron, Cl-, E. coli, Ca+2, Mg+2, No3, Po4 and fluoride contaminations in surface and underground water quality prevailing within and close proximity of the area under current investigation (Biswas et al., 2024; Debnath et al., 2023a&b, Barman et al., 2022; Roy et al., 2021). Concerned about potential environmental risks and pollution arising from the accumulation of geo-genic factors in wetland water have grown over time. The previous works employed various scientific methods, including multivariate statistical approaches and the integrated water quality indices. There is no prior research study to incorporate comprehensive pollution index for wetland (CPIW) and Geoaccumulation index (Igeo) with an inverse distance interpolation approach. With this concern in mind, the main objectives of this study are proposed (1) the present study was aimed to execute the physico-chemical characteristics of surface water samples (2) to investigate the spatial variation of surface water pollution and contamination, and (3) to identify the potential sources of contamination using factor analysis approach. The unique integration of comprehensive indices with spatial mapping through geospatial techniques in the recent work provided a more robust framework for identifying pollution sources. The results of this study will provide stakeholder and policy makers with a comprehensive overview about incorporating modern technologies to enhance cost and time effective ways of managing wetland water quality issues, and develop innovative strategies for sustainable practices.

2. Materials and methods

2.1. Study area description

The present study has been undertaken at Rudrasagar wetland located in the western fringe of Tripura (23°29' to 23°31'N latitudes and 90°18' to 90°19'E longitudes), India (Fig. 1a & 1b). It includes an area of about 1.19 km^2 in Sepahijala District (Fig. 1c). The wetland is situated downstream of the Gomti River catchment. It is a freshwater lake that was declared as the Ramsar site in 2005 for international importance. Rudrasagar Lake is a riverine wetland which is seasonally inundated by three perennial streams; Durlavnarayan cherra (3.2 km), Kamtali cherra (4.1 km) and Noa cherra (15.7 km). Noa cherra is a primary stream originated from the Baromura hill range (about 23°38'27''N and 91°30'36''E) in Gomati District. Considering the seasonal behaviour, the river brought a heavy discharge during monsoon season (June–September) and considerable flow duration persisted till November. Rudrasagar discharges into downstream of the Gomti River through the narrow Kachigang channel. In the month of January–May, the wetland bed remains exposed until the next rainy season. Wetland (Fig. 1d) catchment is predominantly used for agriculture, fishing as well as various economic purposes. Wetland water is frequently utilised for domestic and irrigation purposes. Additionally, it is admired as an iconic tourist destination and is crowned by the presence of the largest Lake palace Neermahal. Currently, it is fully used by more than 2 thousand fishermen families. The catchment consists of a seasonally inundated floodplain fringed by several vegetation patches including aquatic plants, terrestrial plants, weeds, shrubs, herbs and sacred groves. The catchment area is about 130.91 km^2 and diverse in its geology, hydro-geomorphological features and vegetation attributes. Landscape features demonstrate rural and urban characteristics. Rainfall is seasonal with a mean annual temperature of 9.74–38.63°C. Relative humidity is three times higher ranging from 33–91%. The western catchment is relatively shallower than the eastern side (Fig.2a).

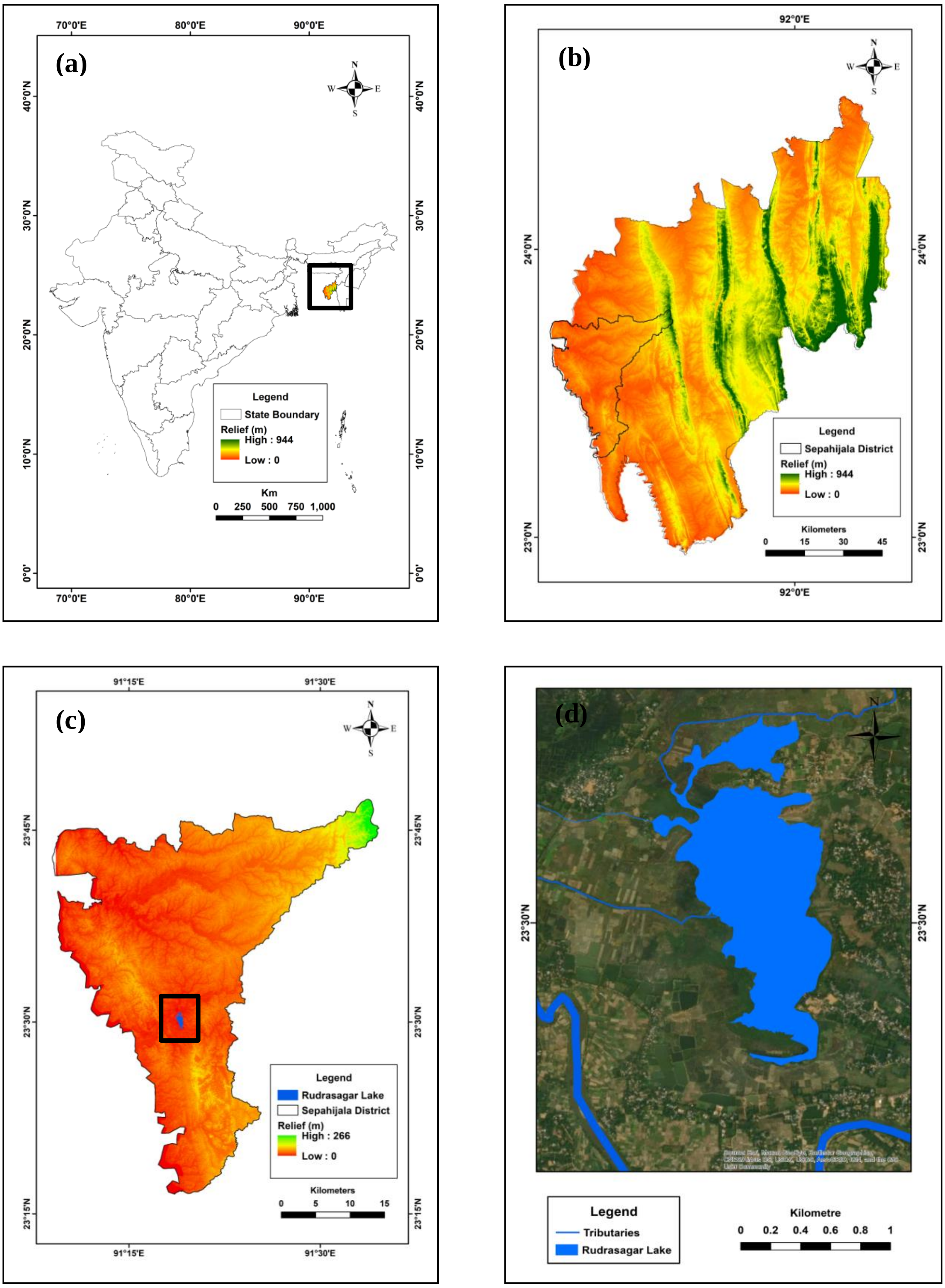


Fig.1: Location map of the study area; (a) Geographical location of Tripura in India, (b) Digital Elevation Model of Tripura and demarcation of Sepahijala District, (c) Relief map of Sepahijala District and identification of Rudrasagar Lake position, (d) Satellite view of Rudrasagar Lake area (Source: prepared by the authors using SRTM DEM and Copernicus Satellite image, 2022)

2.2. Description of sampling sites

Water samples were collected from 24 sampling sites in two different perspectives (peripheral and core sampling sites) to compare between directly impacted (peripheral) and relatively preserved (inner) water quality. The samples were collected to determine the influence of influential tributaries and interior parts of Rudrasagar wetland as denoted with

S1–S24 in Figure 2b. Sampling sites were selected correspondence with their relative distances (500*500 m) approach. Peripheral sites located at the outer boundaries of the water body, these sites are in direct interface with anthropogenic interventions, and potential contamination sources. Similarly inner sites are situated within the central portions of the water body with relatively less external influences (Supplementary Table 1). Sample site S1 is a major attraction for tourists for tourist boat facilities to visit the Neermahal palace, making the site a significant tourist hub and picnicking activities. Small-scale industries including automobile repairing and welding industries contribute contaminants to site S2 through surface run-off. Sites S3 and S4 are located near Ghrantali Madrasa and mostly received non-functional brick field run-off. Sampling points S5 and S12 represented the confluence areas of small rivulets. The sites, S7 and S14 are surrounded by densely built-up

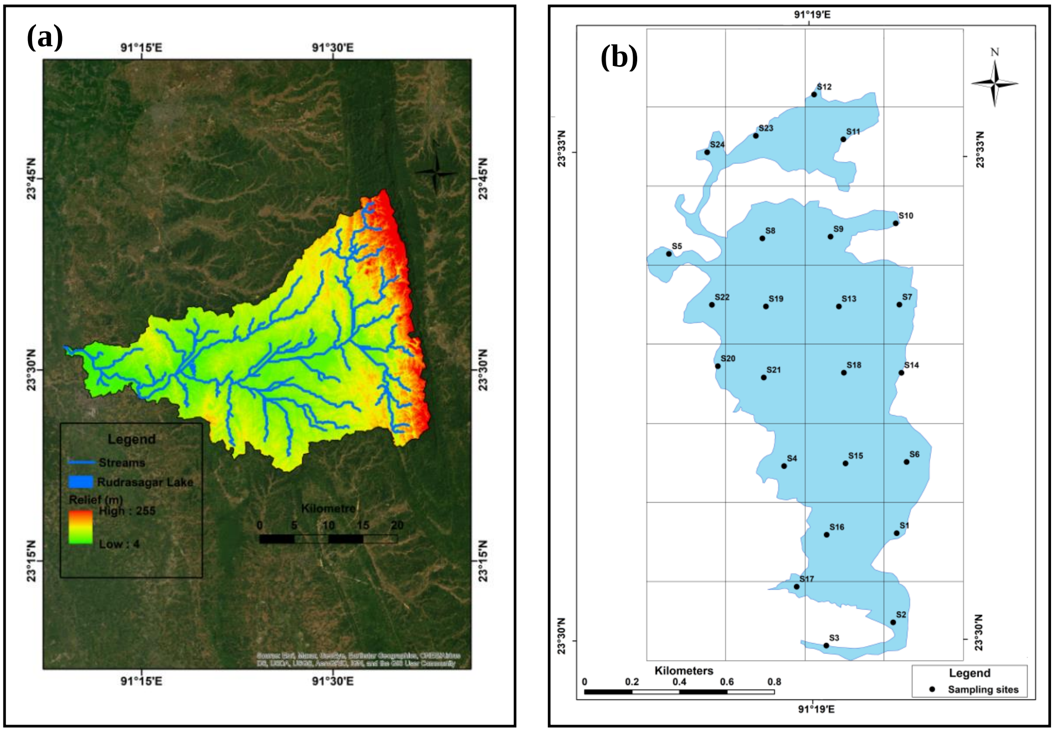


Fig.2: Geographical setting of the study area; (a) Satellite vision and drainage configuration of the catchment area, and (b) Spatial distribution of sampling sites (through Square Matrix)

areas and mostly receive untreated residential and municipal waste. Sampling site S22 is dominated by agricultural activities and contracted with the run-off along with sewerage from the adjacent villages. Most of the anthropogenic activities, including agricultural runoff and household waste discharge, contaminate the wetland water quality through direct and indirect pathways, potentially altering its physico-chemical and biological characteristics. Considering all these features, sites were selected for the analysis of wetland health.

2.3.Sampling design

Monitoring sites has been selected in algebra manner followed by the Square Matrix (SM) developed by several renowned mathematicians (Chang & Chen 2010). The reason for adopting the grid square method is to systematically consider the sampling sites. Moreover, this approach significantly reduces the probability of sampling errors during sample collection, while simultaneously ensuring that each sample is given equal weighted in representing the water body's different zones. Afterwards, monitoring stations were demarked through GPS receivers (Garmin eTrex30x). SM was applied particularly to reduce the discriminate among sampling sites as each sampling site is responsible for the spatial variation of hydro-chemical characteristics. It also ensures that each square grid has an equal possibility of being sampled. First divide the entire wetland following the grid square approach and area was splitting into equal segments. In this study we have designed the square matrix with equal number of rows and columns. It is an n x n matrix, where n represents the number of rows or columns. In this study each grid contains one sampling site and each sample occurs exactly once in each row and each column of the grid. Individual grid is assigned a unique sample ID.

Let us assume that each of square matrix of order 2 × 2 experimental units is to be allocated among one of r treatments with the knowledge of respective information. The observed 2 × 2 dimensional vector is expressed as follows:-

$$\boldsymbol{A_{2*2}} = \begin{matrix} \boldsymbol{a_{11}} & \boldsymbol{a_{12}} \\ \boldsymbol{a_{21}} & \boldsymbol{a_{22}} \end{matrix} \qquad \textbf{(Chang \& Chen 2010)} \qquad \textbf{(1)}$$

In this section we provide an analysis of the square-root (3×3) algorithm for sampling. Square matrix of order 3×3 experimental units is to be allocated among one of r treatments with the knowledge of respective information. Observed (3×3) dimensional vector is expressed as follows:-

$$\boldsymbol{A_{3*3}} = \begin{matrix} \boldsymbol{a_{11}} & \boldsymbol{a_{12}} & \boldsymbol{a_{11}} \\ \boldsymbol{a_{21}} & \boldsymbol{a_{22}} & \boldsymbol{a_{13}} \\ \boldsymbol{a_{31}} & \boldsymbol{a_{32}} & \boldsymbol{a_{33}} \end{matrix} \qquad \textbf{(2)}$$

The previous matrix has a limitation, therefore, Huang et al. (2021) attempt to address the redundancy in the computation of the two aforementioned matrix from several perspectives and assume that each of square matrix of order n × n experimental units is to be allocated among one of r treatments with the knowledge of respective information. Observed n × n dimensional vector is expressed as follows:-

$$\boldsymbol{A_{n*n}} = \begin{matrix} \boldsymbol{a_{11}} & \boldsymbol{a_{12}} & \boldsymbol{a_{13}} & \cdots & \boldsymbol{a_{n1}} \\ \boldsymbol{a_{21}} & \boldsymbol{a_{22}} & \boldsymbol{a_{23}} & \cdots & \boldsymbol{a_{n2}} \\ \boldsymbol{a_{31}} & \boldsymbol{a_{32}} & \boldsymbol{a_{33}} & \cdots & \boldsymbol{a_{n3}} \\ \vdots & \vdots & \vdots & \vdots\ddots & \vdots \\ \boldsymbol{a_{n1}} & \boldsymbol{a_{n2}} & \boldsymbol{a_{n3}} & \vdots & \boldsymbol{a_{nn}} \end{matrix} \qquad \textbf{(3)}$$

Samples were collected from the surface of the water body in pre-cleaned, acid-washed brown-cap amber bottles. Sampling was conducted in triplicate for data validation and analysed twice for more reliability. A weighted average of duplicate water quality data was considered for further evaluation. Few parameters were analysed on the study site and later, samples were transported to laboratory for further analysis maintaining proper preservation protocol. This approach ensured the efficiency and accuracy of data curation, which is essential for understanding hydrological dynamics and characterisation of wetland aquatic health.

2.4.Sample preparation and monitoring parameters

After delineating the sampling sites, samples from surface water were collected in sampling bottles pre-cleaned with hydrochloric acid (HCl), or distilled water (dH2O). Prior to sample collection final rinsing with the sample water at the site was performed. The parameters were carefully chosen after conducting an extensive literature survey published in several peer reviewed journals. Multi-parameter water quality approaches provide advanced and robust practical monitoring solutions for the water quality assessment and hydrological modeling (Shin et al., 2023). At sampling sites, few parameters; pH and electrical conductivity (EC) were measured directly using a sensor-based multiparameter water quality analyser (Hanna probe HI98194). Samples were transported to the laboratory for subsequent processing and analysis preserved in an insulated and ice-cooled container. Afterwards, total dissolved solid (TDS) was estimated using gravimetric approach and parameters such as total alkalinity (TA) and total hardness (TH) were analysed using titrimetric method. Few trace elements such as Sodium (Na), Magnesium (Mg), Calcium (Ca), Potassium (K) and Iron (Fe) were measured

Table 1: Method, and Standards used to analyse the variables

Parameters	Acceptable range	*Threshold limit	Method and instrument used
pH	6.5–8.5	7.5	Multiparameter water quality analyser (Hanna)
EC	250	730	Multiparameter water quality analyser (Hanna)
TDS	500–1000	500	Filtration and weight difference
TA	200	200	Titrimetric method
TH	500	200	EDTA method
Cl	350	250	Titrimetric method
SO4	200	400	Spectrophotometer
Na	200	200#	SEM
Mg	30	100	SEM
Ca	75	200	SEM
K	10	10#	SEM
Fe	1.0	1.5	SEM

* BIS and WHO standards have been considered, 2012
#No threshold limit is explicitly set by BIS/WHO

by scanning electron microscopy (SEM). Though they are major metals presented as nutrients in natural water bodies (Kolarova & Napiórkowski 2021) but also can be defined as trace elements (Dinelli et al., 2012). Analysis was conducted using analytical reagent (AR) grade, in accordance with the standard protocol. Table 1 summarises the analysed parameters, the respective analytical method employed, and the standard values for comparison with the determined parameters. The tolerable limits for various water quality parameters were adopted based on the guidelines provided by the Bureau of Indian Standards (BIS 2012) and World Health Organization (WHO 2012). The exclusion of biological parameters such as E-coli, total coliform, and faecal coliforms in this study is attributed to limitations in available dataset.

2.5.Statistical analysis

IBM SPSS software (v26) and OriginPro 2019 were employed to perform statistical analysis of the samples. The Pearsons Correction Matrix is also performed among the variables to establish a linear interrelation among the parameters. The normality of the entire dataset was assessed using both the Kolmogorov-Smirnov (K-S) and Shapiro-Wilk (S-W) tests at a significance level of 0.05.The Kolmogorov-Smirnov test statistically did not meet the data normality test assumptions; therefore, the Shapiro-Wilk test statistic (W) was prioritised to test the normality of the observed sample data . The formula to calculate *W* is as follows:-

$$W = \frac{(\sum_{i=1}^{n} (a_i x_{(i)})^2}{\sum_{i=1}^{n} (x_i - \bar{x})} \qquad \textbf{(4)}$$

here; *W* is the Shapiro-Wilk test statistic, $x_{(i)}$ was the i^{th} order statistic (smallest to largest), $(\bar{x})$ is the sample mean, a_i is the constant, and *n* is sample size. The results of the data normality

Table 2. Data normality tests among variable concentration

Variables	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df.	Sig.	Statistic	df.	Sig.
pH	.253	23	.001	.831	23	.001
EC	.245	23	.001	.824	23	.001
TDS	.180	23	.053	.916	23	.054
TA	.399	23	.000	.475	23	.000
TH	.169	23	.088	.896	23	.021
Cl	.272	23	.000	.724	23	.000
SO_4	.212	23	.009	.772	23	.000
Na	.114	23	.200*	.965	23	.575
Mg	.177	23	.061	.916	23	.055
Ca	.163	23	.113	.932	23	.120
K	.171	23	.078	.908	23	.037
Fe	.166	23	.099	.915	23	.053

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

tests are presented in Table 2. Certain hydro-chemical parameters, specifically TDS (K-S: 0.053, S-W: 0.054), Sodium (K-S: 0.200, S-W: 0.575), Magnesium (K-S: 0.061, S-W: 0.056), Calcium (K-S: 0.113, S-W: 0.120), and Iron (K-S: 0.099, S-W: 0.053), exhibited normal distribution at the significant level of $p > 0.05$ in both the statistical tests. However, few parameters such as pH, EC, TA, Cl, and SO_4 showed significant deviation from normality *(corresponding* $p < 0.05$*)*. Despite these deviations, the applications of parametric statistical analyses (Pearson correlation matrix and PCA) were assessed. These were justified by several considerations: (i) the sample size (n=24) was adequate and supported the Central Limit Theorem, (ii) the moderate nature of normality does not violate test statistics, (iii) although PCA does not require a strictly normal distribution, severe departures from normality can affect the actual results, (iv) the patterns of the observed results were consistent across both parametric and non-parametric approaches. Moreover, CPIW and Igeo have the advantage that they do not require normally distributed dataset criteria. These findings were aligned with similar hydro-chemical studies where multivariate statistical approaches have been successfully applied to mixed-distribution datasets while maintaining scientific validity.

2.6.Correlation and factor analysis

The 2-tailed Pearson's Coefficient matrix was used in this study to identify the strength of a linear association among the observed parameters using the following formula:-

$$\rho(x, y) = \frac{\sum\left[(x_i - \bar{x})(y_i - \bar{y})\right]}{\sigma x * \sigma y} \quad (5)$$

here, $\bar{x}$ and $\bar{y}$ denotes the mean standard of variables, respectively and is the standard deviation of parameters. Strong positive and negative correlations were determined with the value ±1 while 0 represents no association. Afterwards, Principal Component Analysis (PCA) was applied to reduce data complexity and dimensionality by creating a more reliable dataset and identifying significant correlations among the variables. PCA extracts the Eigenvalues and Eigenvectors with uncorrelated variables. Varimax rotation matrix was used to transform primary or original variables. Coefficients of PCs weighted linear combinations were obtained to measure variation in contribute among the variables under different factors. In this study, coefficients of PCs with an Eigenvalue >1 has been confined.

2.7.Comprehensive Pollution Index for Water (CPIW)

Comprehensive pollution index (*CPIW*) was employed to measure the influence of each variable on pollution levels. CPIW computed primarily assigning a relative weight (R_w) ranging 1–5 to each variable accounted for by their relative impact on the drinking water suitability. Table 3 demonstrated the relative weights (R_w) and weight parameters (W_p) which were computed to determine the effect of each chemical constituent on the overall wetland water quality by Equation 3. Concentration status (S_C), the ratio of the parameter concentration to its respective safe limit for drinking water was determined by Equation 4. Overall chemical concentration (O_w) was assessed using mathematical notation 5. Subsequently, overall *CPIW* was obtained by summarising all the calculated values.

Table 3: Different weight, and standard of variables (Subba Rao, 2012)

Parameters	D_2*	R_w	W_P
pH	7.5	5	0.003
EC	730	2	0.310
TDS	500	5	0.212
TA	200	2	0.085
TH	200	2	0.085
Cl	250	4	0.106
SO4	150	5	0.064
Na	200	4	0.085
Mg	30	2	0.013
Ca	75	2	0.032
K	10	1	0.004
Fe	1.5	3	0.001

*BIS and WHO permissible limit, 2012

$$W_P = \frac{R_W}{\sum R_W} \quad \textbf{(6)}$$

$$S_C = \frac{C_n}{D_S} \quad \textbf{(7)}$$

$$O_W = W_P * S_C \quad \textbf{(8)}$$

$$CPIW = O_W \quad \textbf{(9)}$$

The concentration and standard values of the parameters are represented as C_n and S_n, respectively. *CPIW* was utilized to calculate the contribution of each geo-chemical parameter to water quality. The pollution levels are classified according to the criteria outlined by Chakraborty et al. (2021) and are detailed in Table 4. Five categories have been identified for analysis of *CPIW*.

Table 4: Classification of comprehensive pollution index of wetland water (Chakraborty et al, 2021)

CPIW Range	Classification
<1.0	Insignificant pollution
1.0–1.5	Low pollution
1.5–2.0	Moderately pollution
2.0–2.5	High pollution
>2.5	Very high pollution

2.8.Geoaccumulation index *(Igeo)*

Different studies have emphasised the geochemical mechanism containing wetland water quality in different environmental settings. For instance, Shvartsev et al.(2016) stated that the geochemical aspects of wetland waters should be analysed in a framework of geomorphic, geological, and anthropogenic perspective to better understand their composition, dynamics, and the impact of anthropogenic attributes on the ecosystems integration. Initially, *Igeo* method was developed (Muller 1969) to determine the degree of metal contamination in the bottom sediment and compare current concentration levels with baseline concentration (pre-industrial development). Thereafter, Igeo index was successfully utilised in various fields especially to the measurement of wetland contamination (Esmaeilzadeh et al., 2016; Islam et al., 2015). It involves logarithmic functions and background concentration multiplied by 1.5 (lithogenic effects act as a background factor). In this study, other elements were found to be very insignificant and negligible therefore, Na, Mg, Ca, K and Fe were considered for determination of Igeo. Computation of *Igeo* for trace elements accumulated in the water involved using the in Equation 7, where trace element contamination is characterised on a scale from 0 - 6, depending on its class, as demonstrated in Table 5.

$$I_{geo} = Log_2\left(\frac{C_n}{1.5 * B_n}\right) \quad \textbf{(10)}$$

here, C_n denotes the concentration of metals in the sample; B_n refers to the geochemical factors acting as background contamination levels for the pollutant. The background concentration was determined by computing the geometric mean of observed values. The background concentration is calculated by multiplying all the values together and then taking the nth root, where n refers to the number of observations. The background concentration of variables was determined using the following Equation:

$$B_n = \sqrt[n]{a_1 a_2 a_3 \ldots\ldots a_n} \quad \textbf{(11)}$$

here, $a_1, a_2, a_3 \ldots a_n$ are the individual experiential weights, and n is the number of variables observed in the study. *Igeo* method is valuable for assessing anthropogenic contamination of metals in samples by comparing it with the background concentration of that particular variable. The *Igeo* is divided into seven classes, from unpolluted to severely contaminate. Table 5 comprises seven grades (0–6) representing different levels of metal enrichment above the average shale value, ranging from unpolluted to very highly polluted water quality. So, if the *Igeo* value is negative, it suggests the concentration is lower than the background concentration, indicating a lower level of contamination. In this study, certain parameters exhibit a negative *Igeo* value compared to the background, leading us to ignore these instances under consideration for contamination.

Table 5: Classification of geoaccomulation index (Mular, 1969) for determination of Trace elements in water			
Trace elements	Categories	Igeo range	Level of Contamination
Na, Mg, Ca, K, and Fe	0	Igeo≤0	Practically uncontaminated
	1	0<Igeo≤1	Uncontaminated to moderately contaminated
	2	1<Igeo≤2	Moderately polluted
	3	2<Igeo≤3	Moderately to heavily contaminated
	4	3<Igeo≤4	Heavily contaminated
	5	4<Igeo≤5	Strongly to extremely polluted
	6	Igeo>5	Extremely contaminated

2.9. Spatial interpolation (IDW)

Hydrological characterisation of Rudrasagar surface water quality was conducted through spatial variation mapping corresponding with widely accepted water quality parameters. The physico-chemical dataset has been imported into the GIS database, facilitating spatial analysis and visualisation for a comprehensive understanding of the nature and associations of the variables. The IDW interpolation technique was employed to generate a set of predicted values at known locations within the dataset. It is a highly effective geospatial tool commonly employed for interpolating spatial distribution data and modelling target parameters (Raheem et al., 2023). The spatial variation mapping of wetland water quality parameters was established by employing the inverse distance weighting (IDW) technique, as introduced by Shepard (1968) and denoted in Equation 9.

$$\hat{v}_1 = \frac{\sum_{i=1}^{n} \frac{1}{d_i^p} v_i}{\sum_{i=1}^{n} \frac{1}{d_i^p}} \quad (9)$$

here, $\hat{v}_1$ is the value being estimated for the target location d_{pi} and d_{pn} are the distances between $n - p$ point estimated; vi is the known value for estimating water quality at unknown locations; and n stands for the degree of inverse distance weighting.

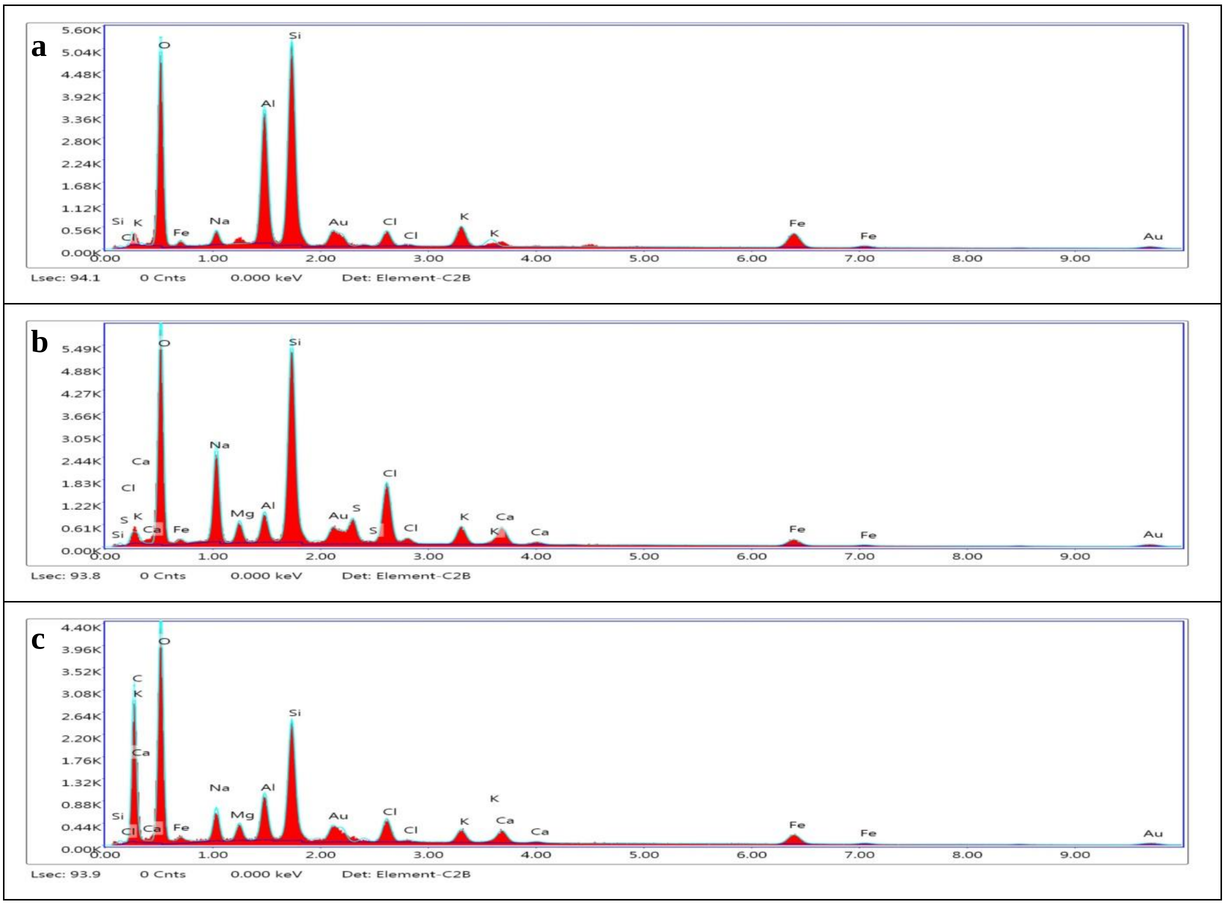
3. Result

3.1. Water chemistry

The recent study evaluated the pollution level and geo-accumulation load of Rudrasagar Lake water. The catchment area continuously experiences high susceptibility and vulnerability due to encroachment associated with human settlements and agricultural practices. As a result of anthropogenic interferences, the water quality of the lake is under serious threat. The physico-chemical variables of twenty four samples were analysed and compared with the preferable drinking water standard by WHO (2012). Consider the observed physico-chemical and trace element concentration of surface water samples with acceptable range and threshold limits. The results revealed that most parameters have a wide range of standard deviations, showing that a variety of activities impacted surface water quality. According to the observed dataset, few of the parameters exceeded the standard threshold limit. Chemical concentration trend among the samples was observed in a hierarchical order of SO_4^{2-}> Cl^-> Na^+> Ca^{2+}> Fe^{3+}> K^+> Mg^{2+}. Spatial analytical tool (IDW interpolation) from geospatial technology was applied for spatial variation mapping of individual parameters (Fig.7–10).

3.2.Trace elements characterisation

Multiple energy-dispersive X-ray spectroscopy (EDS or EDX) spectra of elemental composition of the samples were demonstrated in Figure 3. Each spectrum represented X-ray energy levels, with the peaks corresponding to the properties of the transmitted X-rays of the various elements. The relative heights of the peaks suggested the relative concentrations of these elements in the sample. This type of analysis is commonly used in materials science, geology, and other fields to identify and quantify the elemental composition of samples. The presence of Sodium (Na), Magnesium (Mg), cadmium (Ca), Iron (Fe) and Potassium (K) were observed in most of the samples. Higher concentration of the elements; Al, Si, and O was confirmed from the Figure 3a. The spectrum from Figure 3b indicated the presence of elements like Na, Mg, Al, Si and O while in Figure3c highlighted



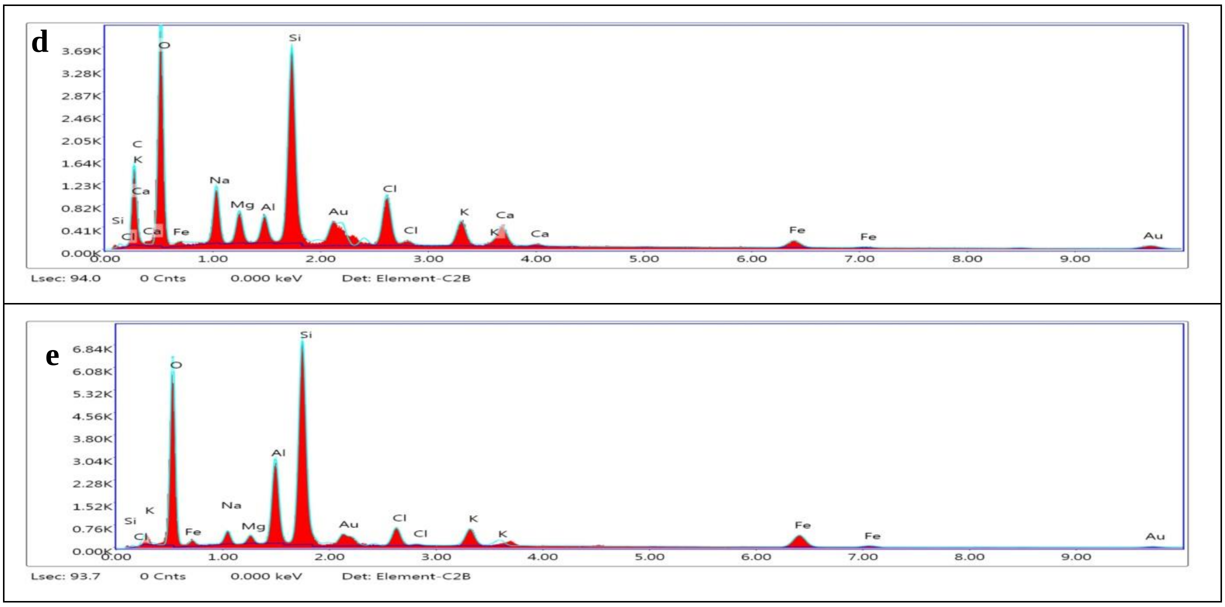


Fig. 3: Electron micrographs of particles from water with accompanying EDX spectra (Scale represents 10 m).

the elements like C, O, Na, Mg, Al, Si, Cl, K, Ca, and Au. Au spectrums were found for the Au coating on the samples (Fig.3d). These spectra provide information about the elemental composition of the samples being analysed, which could be useful for various applications such as material characterisation, quality control, or forensic analysis. Among the samples, Na ranged from 1.59 to 20.11. The total metal content of the lake water ranged from 0.57 to 6.31 mg/L for Mg, 0.01 to 11.20 mg/L for Ca, 0.01 to 6.68 mg/L Fe and 1.23 to 6.23 mg/L for K. The results indicate the presence of higher concentrations of Na than other trace elements (Fig.3e). A long period of aging and water weathering may have led to a substantial increase in trace elements concentrations.

3.3.Statistical analysis

The significant threshold limits recommended by the different organisations have been considered and are outlined in Table 4. The statistical analysis summary includes minimum, maximum along with standard deviation of different parameters of wetland water is illustrated in Table 6. In Rudrasagar Lake, pH ranges between 6.30 and 7.90 indicated water is within a neutral to slightly acidic as well as slightly alkaline in nature. All the analytical samples were within the acceptable range prescribed by WHO (6.5–8.5). Panda et al. (2018) found that water pH is associated with alkalinity and hardness in freshwater ecosystems, and influences the survival of living and non-living organisms. Supplementary Figure 1 illustrates the range of physico-chemical parameters observed in the study signifying the variations in key water quality indicators. The observed lowest pH was at S9 reflecting slightly acidic, while S21 reflects a slightly alkaline in nature. A considerable amount of pH is attributed to agricultural fields and non-functional industries, resulting in a notable amount of pH in the water. EC indicates moderate ionic concentration with significant variability across sampling sites. The range of 69.33 to 652.33 suggested that EC at few sites were within acceptable limits for aquatic ecosystems, while higher levels of EC were recorded at S4. An average of 284.44±199.17 µS/cm (mean±S.D) was observed, as there was a significant difference among other sampling stations. Standard deviation in the observed results of EC highlighted the necessity for localized analysis to identify areas with potential issues. Similarly, TDS levels exhibit a significant range, indicating notable variability in water samples. TDS values ranged widely from 778.93± 187.24 with a standard error of 38.22. The higher values attributed to agricultural fields and brick kiln industries, contributing to a significant increase in total dissolved solids in the water body. The evaluated TH value varied from 6.88 to 348.13 mg/L with an average of 143.36±81.42 mg/L. Subsequently, the central region of this wetland showed lower TH concentration. The TA

Table 6: Descriptive statistics of water quality parameters

Variables	Min.	Max.	Avg.	Std.	Std. Error
pH	6.53	7.90	7.01	0.41	0.08
EC	69.33	652.33	284.44	199.17	40.66
TDS	374.40	994.00	778.93	187.24	38.22
TA	10.79	829.17	186.55	173.59	35.43
TH	6.88	348.13	143.36	81.42	16.62
Cl	1.78	384.34	96.92	112.73	23.01
SO4	0.57	627.54	413.65	207.34	43.23
Na	1.59	20.11	10.48	5.46	1.11
Mg	0.57	6.31	2.56	1.34	0.27
Ca	0.01	11.20	5.16	3.33	0.68
K	1.23	6.23	3.19	0.97	0.20
Fe	0.01	6.68	3.47	2.13	0.44
*All units are express mg/L excluding EC (uS/cm)					

concentration of this study area varied from 10.79–829.17 mg/L. The spatial alkalinity mapping demonstrated that the concentration of alkalinity in water is negligible and samples are below the standard value for drinking purposes. During the study period, the concentrations of sulfate (So4), sodium (Na), and magnesium (Mg), from all sampling sites were 413±207.34, 10.48±5.46, and 2.56±1.34, respectively. The concentrations of Calcium (Ca), Potassium (K), and Iron (Fe) are collected as 0.01–11.20 mg/L, 1.23–6.23 mg/L and 0.01–6.68 mg/L, respectively. It has been noticeable that some of the parameters in a few sampling sites exceeded the standard concentration for drinking water quality.

3.4.Correlation and factor analysis

Carl Pearson's correlation coefficient analysis was used for monitoring datasets to minimise dimensionality, which was helpful in understanding to determine the association among the variables (Fig. 4). Positive relations with statistical significance were shown with blue colour, while negative relations were visualised by red colour. pH established relatively negative correlations with most parameters including EC (r=-0.03), and TDS (r=-0.24) and moderate positive correlation with TH (a r =0.42) significant at $p < 0.01$. pH demonstrated whether the nature of samples are acidic or alkaline which can be altered by H+ ion. The Pearson coefficient(r) of SO4 showed that there was a significant positive association with Na (r=0.40), EC (r=0.35), and TDS (r=0.70) with $p < 0.05$ significance, suggesting that sulfate ions contributed substantially to the total dissolved solid content. Similarly, TA (r=-0.38), pH (r=-0.29) showed negative linear relation in water sample particularly, including TDS (r = -0.46) and total hardness (TH) (r = -0.61) is mainly caused by sewage wastes and surface run-off from solid waste dumping ground. This inverse relationship confined that if alkalinity elevated, there is a tendency to decrease in concentration. The Correlation coefficient of Mg content in water samples demonstrated a strong and significant relation with chloride (Cl) (r = 0.64) and iron (Fe) (r = 0.56) concentration, suggesting potential common geological sources and similar geochemical mechanisms influencing their concentrations. The strong correlation with chloride could indicate weathering of magnesium-rich minerals or possible anthropogenic inputs affecting both parameters simultaneously. Gloomy relationship was found with TA (r=-0.22), TSS (r=-0.12), and K (r=-0.14) at $p<0.01$ significant level (2-tailed). This study proved that the correlation of TDS and SO4 is 0.70, at a significance level at $p < 0.01$, which can be found in Figure 4a. Na shows positive relation with potassium (r=0.54), Electric Conductivity (r=0.21), TDS (r=0.23), TH (r=0.23), and SO4 (r=0.40), respectively. There was no strong significant correlation among the trace elements, suggesting their lack of control in their distribution, source, and transport pathway. Notably, Sulfate (SO4) indicated a significant correlation with TDS (r = 0.70) and suggested that sulfate ion concentration contributed substantially to the total dissolved solid (TDS) content.

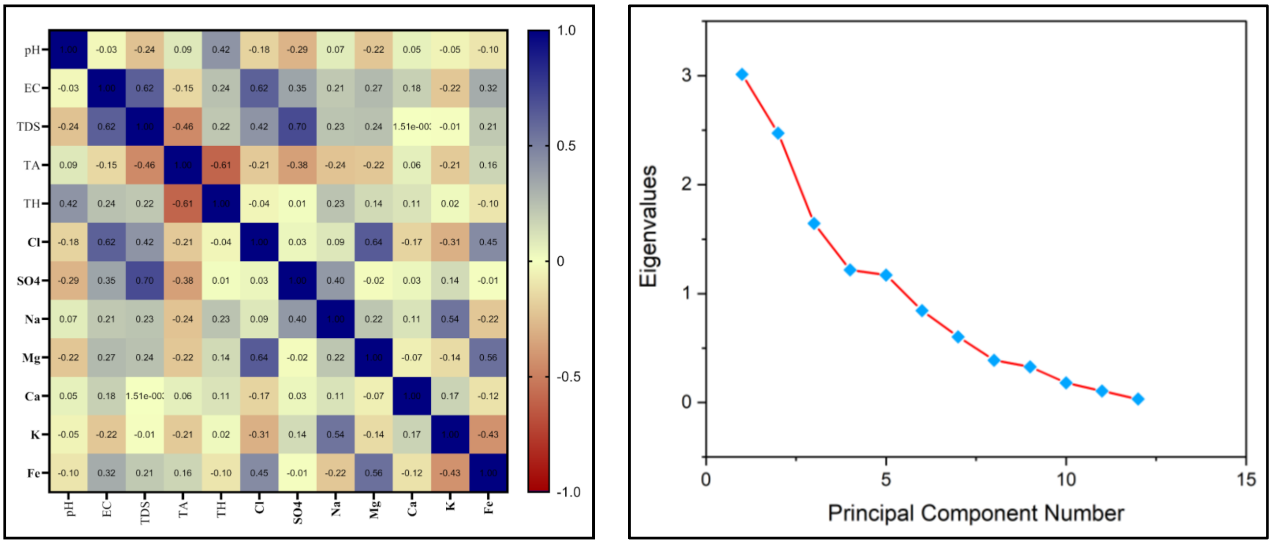


Fig. 4: Presents the (a) Pearson (2-tailed) correlation matrix of the variables at the 0.05 level. and (b) Scree plot illustrate the optimal number of factors loading

This scree plot (Fig.4b) effectively visualized the relative importance of each principal component and helped justify the number of components retained for further analysis. It effectively indicated four principal components to be considered for further interpretation on the contamination sources. Eigen vectors (Table 7) signified the composition of each principal component. In this study, the four components in terms of the original set of twelve observed variables which were primary responsible factors for water quality dynamics. PC 1 consisted of TDS, EC, Cl- and magnesium; this composition was mainly determined by the different variables responsible for water quality (Fig.5a). The first

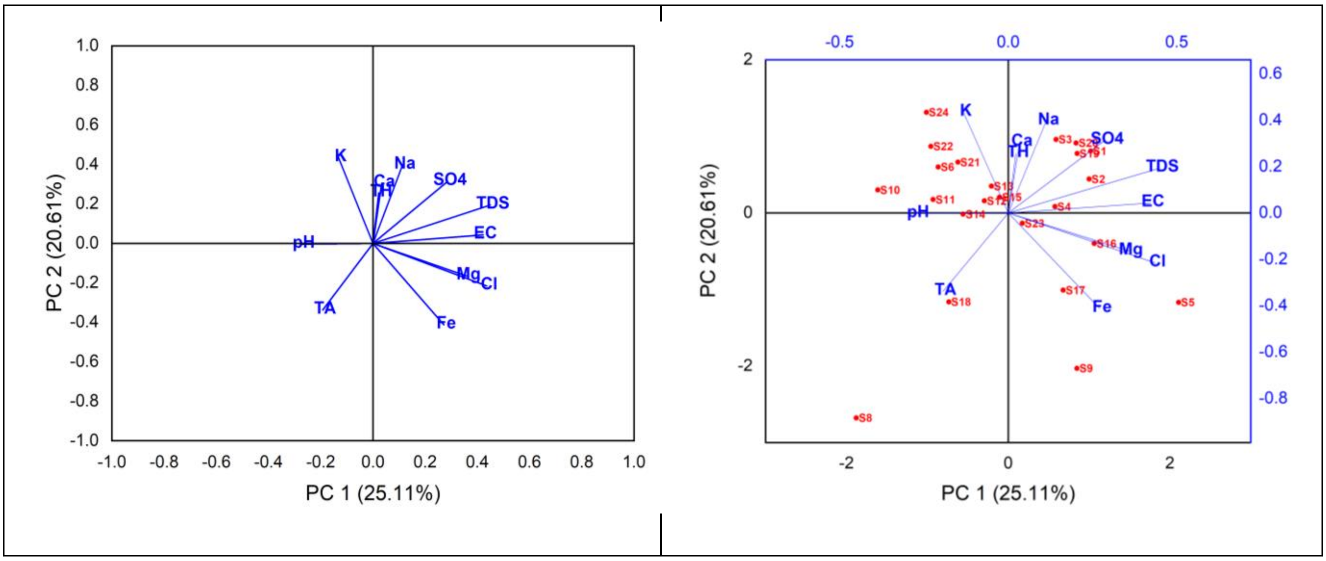


Fig. 5: Principal Component Analysis (PCA) of water quality parameters ;(a) Component Plot matrix and (b) Biplot analysis

principal component (PC1) was heavily influenced by dissolved solids and electrical conductivity. PC2 appeared to be dominated by major cations (K, Na) and showed a strong negative relationship with iron. Combinedly, PC1 and PC2 components accounted for about 45.72% of the total variation in the provided dataset. Similarly, PC3 was characterized by water hardness characteristics. Lastly, PC4 showed strong relationships with specific cations

Table 7:Eigenvalues of the correlation matrix

Component no.	Eigenvalue	Percentage of Variance	Cumulative
1	3.01	25.11%	25.11%
2	2.47	20.61%	45.72%
3	1.64	13.71%	59.42%
4	1.22	10.15%	69.57%
5	1.17	9.75%	79.31%
6	0.84	7.04%	86.35%
7	0.60	5.03%	91.38%
8	0.39	3.24%	94.62%
9	0.33	2.73%	97.36%
10	0.18	1.50%	98.85%
11	0.10	0.88%	99.73%
12	0.03	0.27%	100.00%

(Mg, Na, K), possibly representing specific ionic compositions. This eigenvector analysis helped to identify which parameters contribute most significantly to each principal component and helps understand the underlying patterns in water quality variations. Bioplot (Fig. 5b) demonstrated the relationships between various water quality parameters and the principal components PC1 and PC2. The moderate correlation between Fe and Mg concentrations was confirmed from the biplot, but these parameters showed different behaviours than the other major ionic constituents. The positioning of the variables; pH and

Table 8: Extracted Eigenvectors of the variables

Component no.	Coefficients of			
	PC1	PC2	PC3	PC4
pH	-0.274	-0.003	0.474	-0.127
EC	0.423	0.043	0.101	-0.220
TDS	0.450	0.194	-0.077	-0.291
TA	-0.193	-0.339	-0.253	0.018
TH	0.022	0.255	0.645	-0.127
Cl	0.436	-0.216	0.103	0.215
SO4	0.287	0.314	-0.386	-0.301
Na	0.113	0.397	-0.018	0.474
Mg	0.357	-0.165	0.220	0.516
Ca	0.034	0.304	0.181	-0.101
K	-0.132	0.434	-0.185	0.440
Fe	0.272	-0.413	0.063	0.043

TA in different quadrats from the main ions suggested that those components have independent behaviour in the aqueous system. This approach employed multivariate PCA effectively isolated the complex interrelations among hydrochemical parameters and separated both their clustered and independent behaviours. Such statistical decomposition is useful to understand controlling factors in water quality variation and potential source identification.Table 8 shows the computed factor loadings, percentage of variation, and cumulative percentage explained by each factor/component.

3.5. Status of Rudrasagar health

A comprehensive pollution index was used to assess the impact of pollution on water quality using different variables, while Igeo was utilised to determine the trace element contamination. CPIW ranges from 0.41−1.12 with an average 0.81±0.23 (mean±Sd) and the highest CPIW was observed at S7 while the lowest was observed at the lake periphery where animal excreta and residential waste discharge directly into the lake. The value of Igeo differs from 0.01−2.36 with an average of 0.94±0.72 **(Fig. 6).**

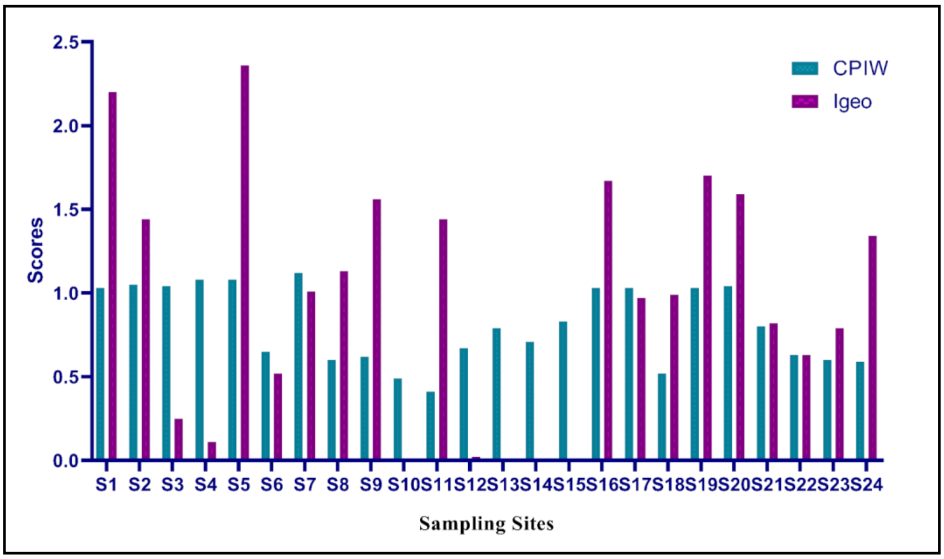


Fig. 6: Determination of CPIW and Igeo of the study area

4. Discussion

This recent study was on the water quality of Rudrasagar Lake by applying a comprehensive pollution index and geoaccumulation index as this site is a hotspot for increased anthropogenic activity. Sampling was done from peripheral and core sites to prove significant spatial variation of the variables. Peripheral sampling helped to determine the external influence on wetland health from the surrounding land-use such as settlements, industries, and agriculture while core sites were affected by fishing and boat routes. This provides insights into the adverse effect of human actions on the water quality dynamics at the wetland edges. Results of the recent study attributed that the study area was highly influenced by different anthropogenic activities posing a serious threat to the wetland ecosystems and was supported by Debnath et al. (2023b); Chawaka et al.,2017. Internal processes like decomposition of organic matter, nutrient cycling, and interactions with wetland vegetation can influence water quality within the wetland itself. Initially the wetland was used for fishing purposes and at that time the wetland water quality was safe and less polluted. Over time, the population started to increase slowly due to immigration and other socio-demographic factors and a township was built-up resulting in a catchment area transformation from fishing ground to agricultural field. Considering the information shared by local villagers, Rudrasgar Udbastu Fishermen Samabay Samity (RUFSS), and local stakeholders, various human activities like livestock manure production, tourism practices accelerating to rising motor boats traffic, and solid waste generation have been progressively affecting the wetland health. In the study area, most of the sampling sites did not cross the upper pH limit of 7.5 according to BIS (2012) while only 5 (21%) of sites have crossed the threshold. Additionally, sampling sites S4, S8, S10, S11, and S21 demonstrated values exceeding the recommended water quality guidelines. The IDW interpolation method helped to identify western side of the wetland with higher pH while the eastern side had relatively better pH concentration (Fig. 7a). This study aligned with the findings of the prior research conducted by Phiri et al. (2005). The study reveals that municipal and industrial discharge can introduce alkalinity in lake water by increasing salt concentration, which also leads to higher pH in water. Spatial electrical conductivity concentration mapping demonstrated almost similar trends as pH. Nine sampling sites showed higher EC than the threshold limit for drinking water. The sampling sites S3, S4, S7, S16 and S17 (Fig. 7b) showed higher values (>500 μS/cm) in south-western region. This elevated EC levels may be attributed to increased dissolved ions, for the presence of large agricultural fields, industrial effluents, waste segregation ground and Jak fishing grounds within the catchment. South-eastern region of the lake was observed to have comparatively lower EC level to others (300-500 μS/cm). Most of the wetland particularly in northern and eastern locations indicated a lower concentration of EC (<300 μs/cm). Previous studies find that rates of urbanisation and industrialisation affect the EC in water (Igbinosa and Okoh 2009). Plate 1 illustrated the predominant anthropogenic activities occurring in and around the peripheral areas of the Rudrasagar wetland.

Plate 1: Anthropogenic Pressures on the Rudrasagar Wetland Ecosystem; (a) Catchment area specifically devoted to paddy cultivation, (b) Wetland used for grazing purposes, (c) Tourist enjoying activities with various equipment, (d) Solid waste generated after idol immersion, (e) Boats ready for fishing, (f) Residential waste directly discharged through the sewerage system, (g) Lake water used for poultry farming, (h) Coconut shells produced by tourists visiting Neermahal and (i) Manure discharged directly into wetland from piggery farms.

The interpolation method indicated spatial concentration of TDS in the study area which shows that the western part of this wetland is highly affected by a higher concentration (Fig. 7c). Most of the study sites exceeded the permissible range of TDS in water of 500 mg/L by

BIS standard and about 50% of the sampling sites exhibited higher TDS concentrations (>500 mg/L). Only five sites (S6, S8, S11, S18, S22 and S24) were under the threshold limit. TDS concentrations are likely to increase dissolved particles attributed by various developmental activities including urbanization, agricultural runoff and industrial discharges. These activities contribute to the leaching of salts, minerals, and other dissolved substances into water bodies and changes their chemical composition. The variability mapping also reflected localized differences in land use, soil characteristics, and proximity to pollutant sources. This study brings into line with the findings of the prior research (Kumar et al., 2014; Bhattacharya et al., 2014) and also found the influx of materials such as clay, plaster of paris, bamboo, rich stews, synthetic cloth, and colour used for idol making in water after being decompose and thus contribute to increased levels of dissolved solids in the water body. The higher alkalinity (>400 mg/L) indicate potential issues with the wetland health (Fig.7d) it can negatively impact aquatic life and disrupt natural ecological balances (Boyd et al., 2016).

Spatial variation mapping appeared to show that low TH concentrations (<100 mg/L) were found at the core of wetland. At the meantime, peripheral sampling sites were more vulnerable and at higher risk of contamination. S10 and S11 (Fig. 8a) have higher hardness concentration and failed drinking water criteria. These sampling site suffering from the presence of residential waste and livestock excreta and manure in both sites as manures, excreta and other pollutants discharge directly into the lake water (Shashvatt et al., 2017). Recently, manure discharge into the water bodies from livestock farming have also been widely prevalent and become a widespread issue. Comparable result also was reported by Xu et al.(2023) and concluded that point and non-point source are responsible for the hardness concentration in the aquatic environment. The chloride (Cl) concentration does not appear to be a significant risk factor based on the information provided in Figure 8b.This study signified that vulnerable and susceptible zones need immediate surveillance and monitoring to identify the potential sources to mitigate the adverse impacts. Spatial distribution of trace elemental (Na, Mg, Ca, K) and nutrient concentration (SO4) provided a clear narrative result highlighting areas of concern and potential risks. The study showed that they contribute very little to water quality contamination. Sulfate concentration was significantly higher in the southern and central parts of the wetland. SO4 concentration levels above 400 mg/L indicated critical zones that are mostly affected by agricultural runoff and industrial effluents (Fig.8c). Moderate concentrations extend towards the northern and peripheral zones, while low concentrations are confined to smaller, less-disturbed areas in the north-eastern part of the wetland. High levels of sulfate in the southern region indicate increased susceptibility. The Na levels are within the acceptable range, indicating the wetland is not facing major sodium-related water quality issues (Fig.8d). Similarly, the southern and central regions indicated sodium levels more than 15 mg/L. These areas are very sensitive to soil degradation from the industrial area. Magnesium levels were predominantly nominal in the study area with isolated high-concentration zones in the southern and few peripheral areas (Fig.9a). Magnesium distribution was indicating localized anthropogenic impacts in the wetland. The spatial

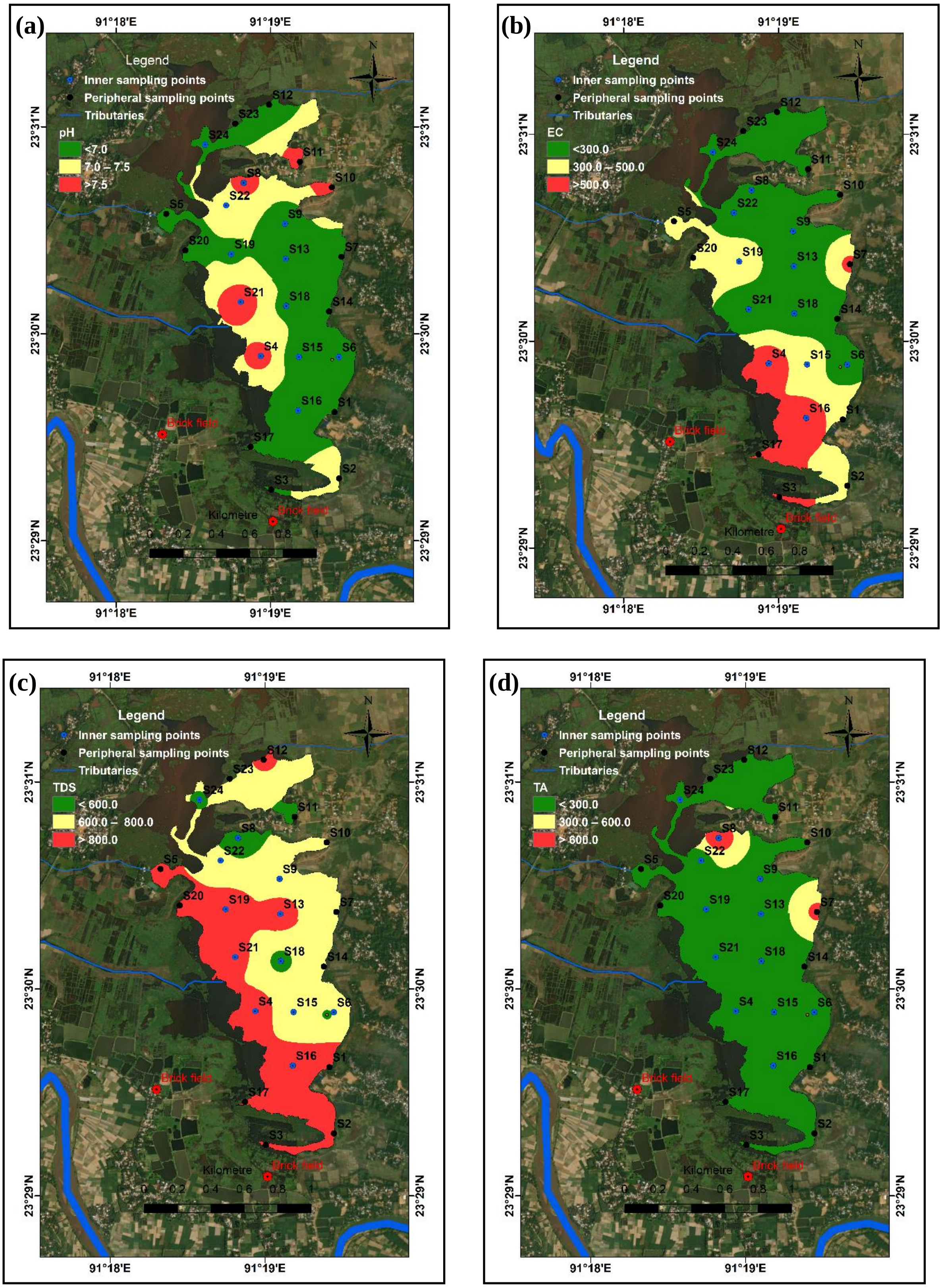


Fig. 7: Spatial variation of Physio-chemical parameters, and zonation using IDW method (a)pH, (b) EC, (c) TDS, and (d) TA

distribution of Ca showed similar trends as Mg concentration. In the study area, about 21 (88.0%) samples were under the threshold limit and only 3 (12.0%) samples exceeded the highest limit of Ca and Mg. BIS set the highest limit of Ca as 75 mg/L, and calcium concentration varied from 0.01−11.20 mg/L with a mean value of 5.16 mg/(Fig. 9b). It shows

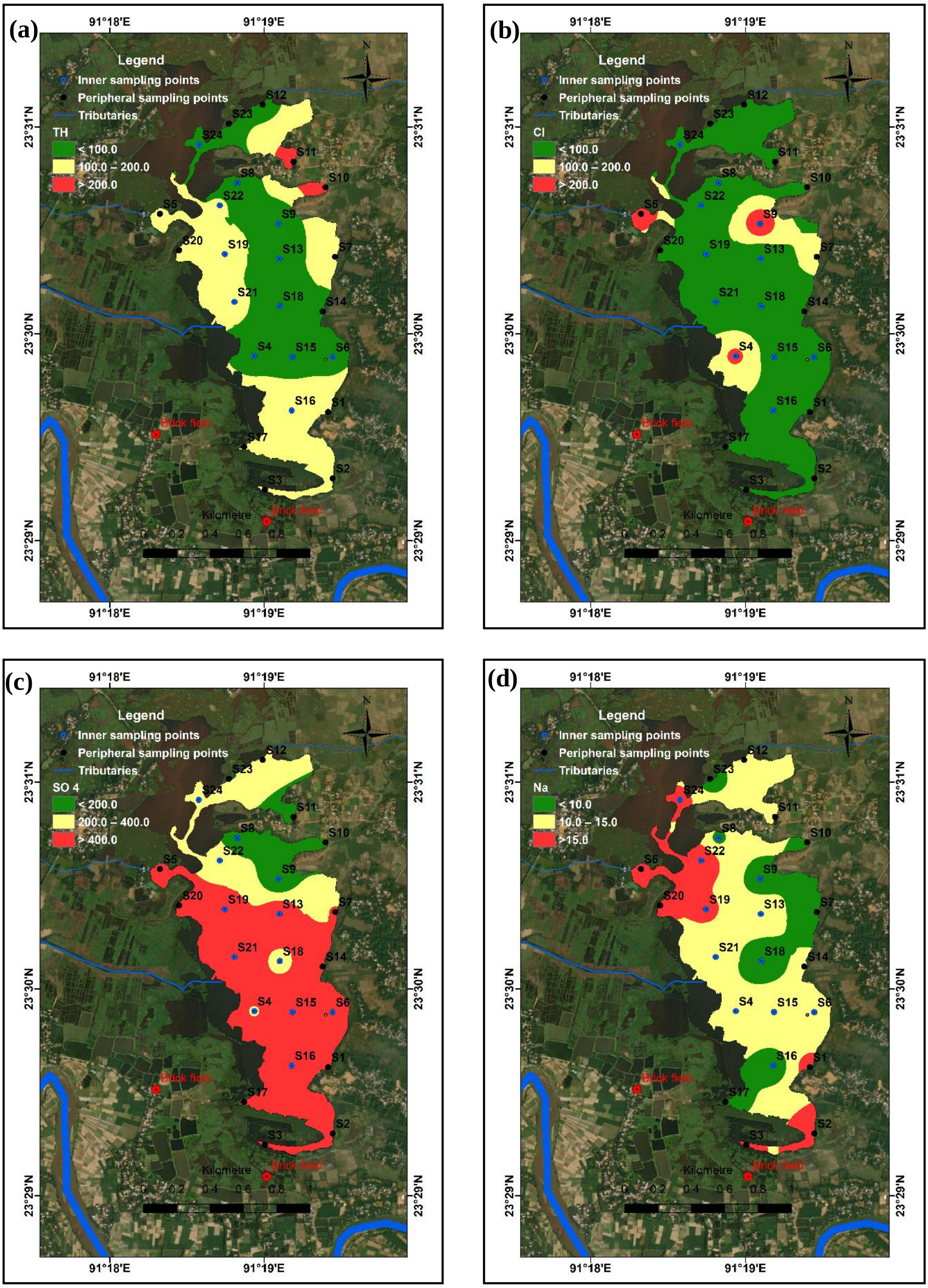


Fig. 8: Spatial variation of Physio-chemical parameters, and zonation using IDW method (a) TH, (b) Cl, (c) SO4, and (d) and Na

significant spatial variability likely influenced by geological and anthropogenic factors. The contribution of calcium is minimal, and no samples surpass the boundary limit for drinking water guidelines. Similarly, the concentration and distribution trends of potassium (Fig.9c)

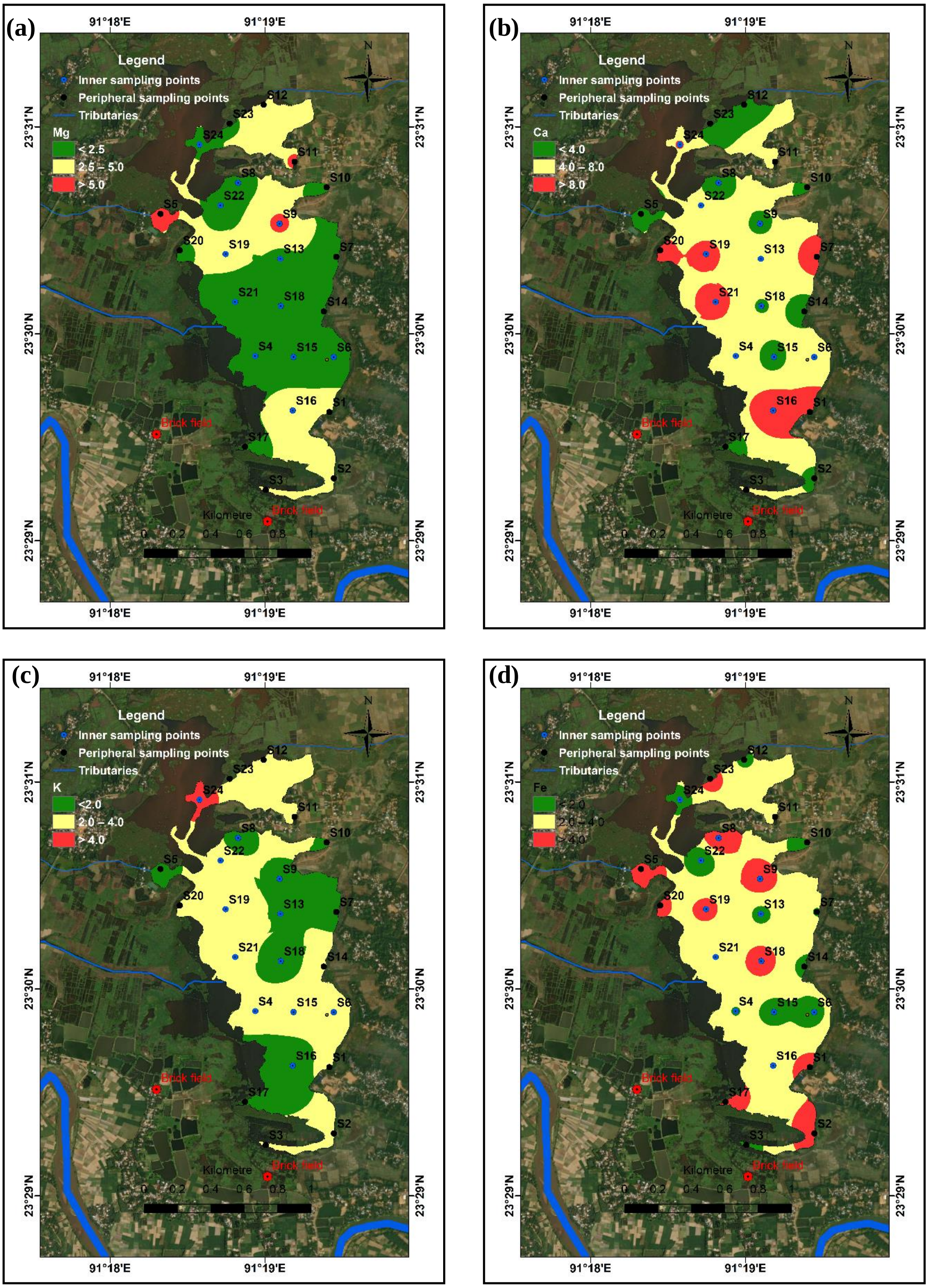


Fig. 9: Spatial variation of Physio-chemical parameters and zonation using IDW method (a)Mg, (b) Ca, (c) K, and (d) Fe

exhibit observations similar to those of iron (Fig.9d). The comprehensive pollution index offers a holistic approach to evaluate the overall pollution level by considering multiple parameters while Igeo determines the heavy metal contamination. Spatial mapping identified the areas in red colour appear to have the highest levels of concentration. These regions likely face greater vulnerability and higher risk within the wetland ecosystem. The spatial variation of the CPIW and Igeo has been illustrated in Figure 10a. The result of CPIW completely indicates that the higher CPIW was observed at the densely populated area. Industrial, municipal waste and surface run-off from agricultural fields stimulate the deposition of contaminants and lead to increased CPIW score. This spatial illustration helps to identify the proper sources accompanied with different patterns of pollutant deposition in the lake sediments, offering a perspective on environmental changes. These findings of the study supported the results of previous studies by Biswas et al. (2024) where it is attributed that the study area is highly degraded by several non-point pollution sources.

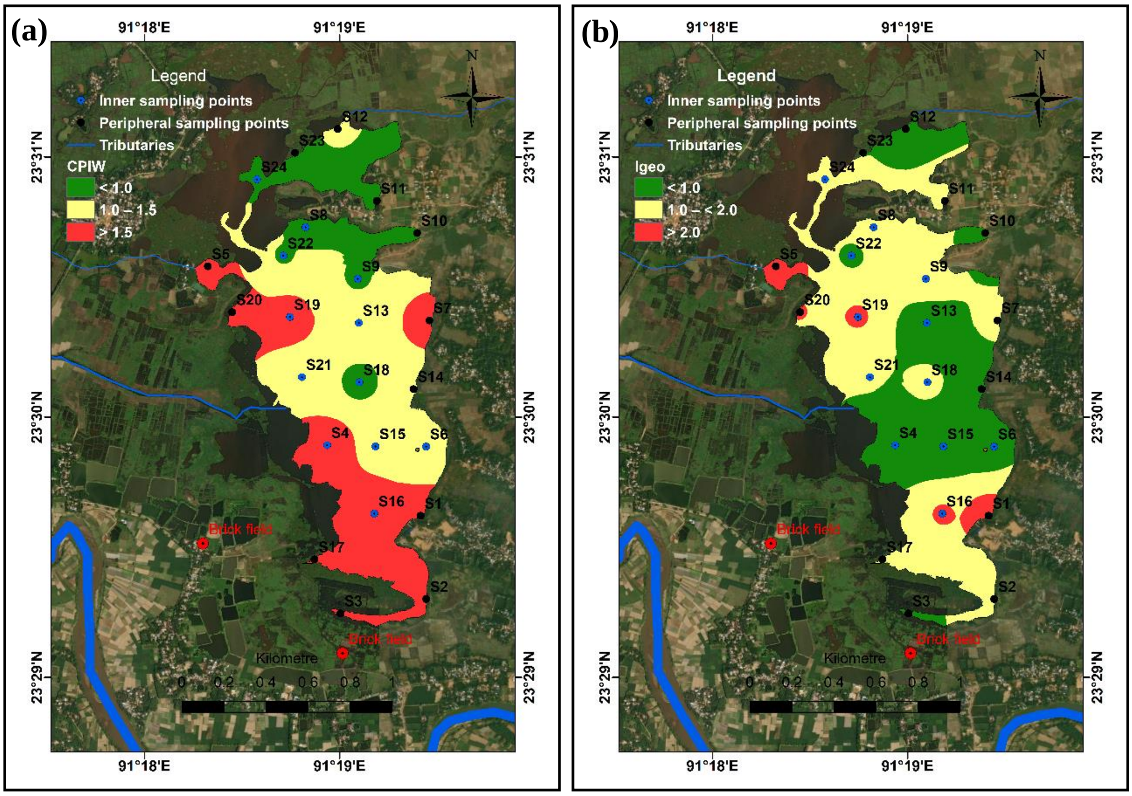


Fig. 10: Spatial variation of Hydro-chemical zonation using IDW method (a) Water pollution based on CPIW, and (b) Trace elements contamination based on Igeo

The sites which are administered as idol immersion sites (S5) and tourist influence site (S1) are indicate higher Igeo value. The red zones in the map indicate areas with higher Igeo values, suggesting these are susceptible to contamination (Fig. 10b). Antizar-Ladislao et al. (2015) evaluated trace metal contamination and toxicity in sediments which are likely attributed to environmental risks associated with increased tourism pressure and idol immersion activities. Heavy metals are being used in several paints and varnish that are sincerely used in idol making (Ujjania and Multani 2011). Further, these sites of agricultural activities increase nutrient and trace element concentration that increase the geoaccumulation score (Looi et al., 2019). Unfortunately, the average depth and catchment area of the wetland are decreasing due to human interference, such as agricultural practices in its catchment areas, sewage disposal, and sedimentation from the upper wetlands. This wetland is considered a resource treasure house and continuously supplies water for domestic use and irrigation. Simultaneously, it is experiencing rapid development as a tourist destination in India and demand tourism-related services. We assess the water quality in this study area to understand the effectiveness and reliability of local wetland services.

5. Conclusion

This scientific study concluded that the effluents of lakeside residential areas and agricultural practices have a major harmful effect on the lake water quality. Zonation by the CPIW method indicates that the physico-chemical conditions have adversely altered the western and south-western regions of this wetland. North and north-eastern parts of Rudrasagar Lake are affected by lower to moderate pollution zones. Inflow water greatly affects the physio-chemical dynamics of the water body. On the contrary, Ca and Mg are not notably elevated as they predominantly reflect the background concentration and are distributed due to depletion of mineral enrichment as substantial enrichment. Results indicate that the overall quality of Rudrasagar wetland is unsafe for drinkable and domestic practice in this study site. Moreover, the physical characteristics of the water differ a little in the sampling sites and are located close to the confluence of the tributaries. However, it is necessary to conduct in-depth assessment of wetland water quality and take measures to enhance the utility of precious resource of water. Hence, it is important to priorities the sustainable management, conservation and utilisation of the wetland ecosystems for long lasting benefit by the local communities. In summary, combining peripheral and inner sampling provides a holistic approach of water quality management in a wetland predominated by inhabitants, considering both point and non-point pollution sources. This comprehensive understanding is crucial for effective management and restoration of wetland ecosystems.

Declaration

Authorship contribution statement

Authorship contribution statement: PD: Geospatial mapping and designed the original manuscript; AB: Conceptualisation, data curation, and formal analysis accompanied by cartographic representation; PC: Provide critical review and supervise the study at the initial stage; SM: investigation, review and editing the manuscript. All authors have carefully gone through the result and discussion section and give their consent to publish the manuscript in this current format.

Acknowledgement

The authors are thankful to Ms. Satarupa Bharadwaj and Postgraduate dissertation students, Regional Planning and Urban & Rural Development laboratory, Department of Geography and Disaster Management, Tripura University, for their assistance during the sample collection. The authors are grateful to Mr. Gouranga Chakraborty, Manager, Rudrasgar Utbastu Fishermen Samabay Samity (RUFSS) for his constant support during the study period. The authors acknowledge Central Instrumentation Center (CIC), Tripura University for providing resources (SEM) for heavy metal analysis and Professor Debasish Maity, coordinator, Department of Biotechnology(North East Region), specifically for laboratory facilities.

Funding Agency

Department of Biotechnology Technology (DBT), Government of India, Vide No. (BT/PR25459/NER/95/1341/2017) provided financial support for data collection, laboratory analysis and research facility

Data availability

All data generated and analysed (Data curation) during this study are included and attached in this article.

Declaration of Competing Interest

The authors confirm that there are no known conflicts of interest associated with this publication.

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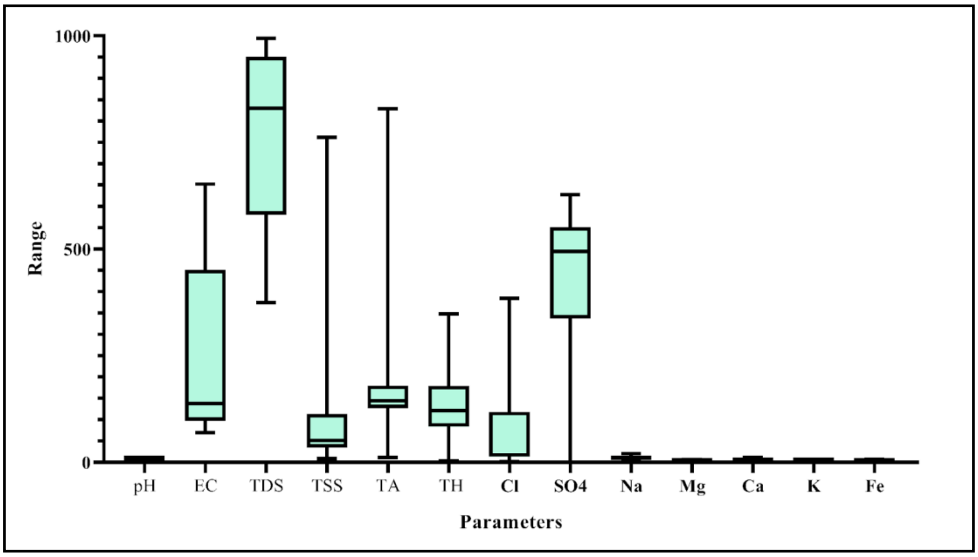
Supplementary file

Supplementary Table 1: Monitoring sites along with significant pollution sources				
Sample ID	**Locality**	**Geo-coordinates**	**Nature of Sampling sites**	**Pre-dominant Pollution Sources**
S1	Rajghat	23° 29' 45" 91° 19' 11"	Lake Periphery	Discharge and dumping of tourism waste, oil spill from motor
S2	Devnagar	23° 29' 33" 91° 19' 11"	Lake Periphery	Sewage inflow into lake water
S3	Ghrantali	23° 29' 29" 91° 19' 02"	Lake Periphery	Discharge of untreated wastewater from non-functional brick field
S4	Near Indranagar	23° 29' 54" 91° 18' 56"	Lake Inner Side	Utilisation of fish feeds and the practice of depositing leaves in fishing grounds
S5	Dashmirghat	23° 30' 23" 91° 18' 40"	Lake Periphery	Plastics, flowers, ornaments and other waste from post-idol immersion
S6	Subhasnagar	23° 29' 53" 91° 19' 16"	Lake Inner Side	Post idols immersion waste
S7	Yubrajghat	23° 30' 16" 91° 19' 13"	Lake Periphery	Urban sewage discharge, Post idols immersion waste
S8	Neermahal front side	23° 30' 25" 91° 18' 53"	Lake Inner Side	Discharge of tourism waste, Oil spills from motor boats
S9	Near Old Rangamura	23° 30' 27" 91° 19' 03"	Lake Inner Side	Waste disposal from animal husbandry and farming
S10	Old Rangamura	23° 30' 27" 91° 19' 11"	Lake Periphery	Discharge of animal excreta and manure
S11	New Rangamura	23° 30' 39" 91° 19' 04"	Lake Periphery	Animal excreta and residential waste
S12	Letamura	23° 30' 45" 91° 19' 00"	Lake Periphery	Agricultural waste
S13	Near Katamura	23° 30' 16" 91° 19' 04"	Lake Inner Side	Emissions of oil spills from motor boats
S14	Gulmurarghat	23° 30' 08" 91° 19' 12"	Lake Periphery	Untreated residential discharge
S15	Near Subhasnagar	23° 29' 54" 91° 19' 04"	Lake Inner Side	Oil spill emissions from motor boats
S16	Near Rajghat	23° 29' 45" 91° 19' 02"	Lake Inner Side	Using fish feeds and arranging leaves and branches in fishing areas
S17	Indranagar	23° 29'38" 91° 18' 56"	Lake Periphery	"Discharge of untreated wastewater from non-functional brick kill

				industry
S18	Near Barakmura	23° 30' 07" 91° 19' 04"	Lake Inner Side	Emissions of oil spills from tourist boats
S19	Near Baidyamura	23° 30' 16" 91° 18' 54"	Lake Inner Side	Employing fish feeds and stacking leaves and branches of trees as part of fishing practices
S20	Battali Bazar	23° 30' 08" 91° 18' 47"	Lake Periphery	Periodic market waste
S21	Near Lengtdarga	23° 30' 06" 91° 18' 53"	Lake Inner Side	Utilising fish feeds and stacking leaves and branches in fishing practices
S22	Near Kachigang	23° 30' 16" 91° 18' 44"	Lake Inner Side	Agricultural waste discharge
S23	Rajendranagar	23° 30' 39" 91° 18' 52"	Lake Periphery	household discharge including cremation site waste
S24	Backside of Neermahal	23° 30' 37" 91° 18' 46"	Lake Inner Side	Residential and municipal waste
Source: Sampling sites demarcation and coordinates retrieved using Garmin (eTrex 30x) GPS receiver, 2022				

Supplementary Figure 1



Supplementary Fig. 1: Range of Physico-chemical parameters observed from the study