Water and Environmental Sustainability (WES)
ISSN: 2710-3404
DOI: 10.52293/WES.4.2.5270
H o m e p a g e: https://www.journalwes.com/

ORIGINAL RESEARCH PAPER

Evaluating semi-arid lake water quality. A synergy of water quality indices, multivariate statistics and geospatial technology

Shantha Kumar Dhanush[1]*, Mahadeva M Murthy[1], Ayyappa Sathish[2], Rinku Verma[1]

1. Department of Forestry and Environmental Science, University of Agricultural Sciences, GKVK, Bangalore, Karnataka, India;

2. Department of Soil Science and Agricultural Chemistry, University of Agricultural Sciences, GKVK, Bangalore, Karnataka, India;

A R T I C l E I N F O

Keywords:
Water pollution
Principal component analysis
The Canadian Council of Ministers of Environment water quality index
Industrial water quality index
Gubbi lake
Tumakuru

Corresponding Author:
academiadocd@gmail.com

Article History:
Received: 19 Nov, 2023
Revised: 16 Dec, 2023
Accepted: 22 Dec, 2023

A B S T R A C T

A study was conducted on Gubbi Lake to investigate the water quality using water quality indices (WQI), multivariate statistical technique and geospatial technology. 20 lake water samples were collected during pre-monsoon and post-monsoon seasons for examining physicochemical parameters. The results revealed that Biochemical Oxygen Demand measured in milligram per litre (8.5 mg/l and 5.3 mg/l in pre-monsoon and post-monsoon season respectively) exceeded the normal range of 5 mg/l and ammonia (1.24 mg/l and 0.6 mg/l during pre-monsoon and post-monsoon season respectively) exceeded acceptable limits recommended by the Bureau of Indian Standards in both seasons. The Canadian Council of Ministers of Environment WQI ranged from 66.7 to 81.13 with a recorded mean of 74.22 imparting 'fair' conditions. Apart from Kelly's index, all the irrigation WQIs designated majority of water samples as suitable for irrigation. All the industrial WQIs conveyed the tendency to corrode except Larson and Skold index that indicated corrosion potential. The principal component analysis effectively diminished the complex water analysis dataset into 6 principal components each for pre-monsoon and post-monsoon seasons which explained 87.85 % and 89.80 % of total variance respectively. These components identified the pollution sources as primarily originating from anthropological activities like agricultural runoff, domestic sewage waters and natural weathering of rocks. Hence, the combined approach using above-mentioned methodologies proves to be indispensable in evaluating surface water quality. The findings of this study further underscore the necessity for prompt action by decision makers for well-being of both environment and public health.

Introduction

At a global scenario, the water requirement for various purposes is estimated at about 4,600 km^3/year which is predicted to increase by 20% to 30% (5,500 to 6,000 km^3/year) by year 2050 (Burek et al., 2016). According to He et al. (2021), the urban population facing water scarcity is projected to 1.7 to 2.4 billion people in 2050 across the globe, with India predicted to be the most severely affected. Around 80% of population facing extreme water stress are living in Asian continent prominently in Northeast China, India and Pakistan (Vanham et al., 2021). These alarming facts have triggered a spark among water scientists to come up with an integrated approach where water quality index (WQI), multivariate statistical techniques and geospatial technology are combined for efficacious water management and monitoring program.

The water quality assessment of a lake is contingent upon physical, chemical and biological characteristics of water which furnish invaluable insights into geochemical processes, water typology and categorization for varied utility purposes (Elsayed et al., 2020). The suitability of water for various purposes like consumption, irrigation and industrial usage has to comply with specific physical and chemical standards to ensure safe and optimal usage and hence assessment of physicochemical properties of lake water becomes mandatory (Shivayogimath et al., 2012). These analytical studies result in large quantities of water quality parameter data and due to its complexity, it is difficult and challenging to come to meaningful conclusions on water quality status and further this situation is exacerbated by seasonal variations.

One of most efficient ways to monitor water quality is by employing water quality index (WQI) models pioneered by Horton (1965) and Brown et al. (1970). Although several national and international standards with desirable and/or permissible limits are derived to judge the water quality, it only speaks about individual parameters which is difficult to comprehend by general public and decision makers. To overcome this, WQI model represents the most preferred mathematical tool to transmogrify huge water characterization data into simple, stable and unitless number that represents the overall status of water quality (Ma et al., 2020). The CCME WQI is most extensively used method endorsed by United Nations Environment Programme Water Programme as it is advantageous due to its simple calculations, tolerance towards absence of data, and flexibility in using water quality parameters (Benkov et al., 2023). Many academics have used CCME WQI methods in their studies (Rahman et al., 2021; Alexakis, 2022; Benkov et al., 2023). Apart from drinking purpose, the lake water is an important source of irrigation and industrial applications. Sodium absorption ratio, percentage sodium, residual sodium carbonate, magnesium hazard, permeability index and Kelly's ratio are widely used irrigation WQI models (Egbueri et al.,2021). The industrial WQI's includes corrosivity and scaling indexical models viz., chloride-sulphate mass ratio, Larson-Skold index, Langelier index, Puckorius scaling index, Aggressive index and Ryznar stability index (Shil et al., 2019).

The multivariate statistical techniques have been exercised to point out possible source of pollution, to quantify spatial temporal variations and existing trends in water characteristics and to get holistic vision of parameters. It reduces the complexity of water quality data and aids in providing rapid and more meaningful solutions (Abdulsalam et al., 2022). In this study, principal component analysis (PCA) is used to furnish the valuable information on the most significant parameters which describe the entire dataset (Mir and Gani, 2019; Sun et al., 2019; Elsayed et al., 2020; Azhari et al., 2023).

The incorporation of analytical results in a GIS software can significantly aid in betterment of visualizing research results and strengthen the water quality management and monitoring process (Ma et al., 2020). IDW (inverse distance weighted) interpolation method is most commonly practiced in spatial analysis that uses combined set of sampling points that are linear weighted to calculate cell values. This method is used to create WQI maps to cover the entire lake surface area in present study.

This experiment is carried out on lake Gubbi in Tumakuru district of Karnataka state, India. The Gubbi lake is situated in rural area at a distance of about 20 kms from Tumakuru city and is an important source for irrigation, commercial fisheries and domestic purpose. Gubbi taluk is home to population of about 262,518 people practicing agriculture as main occupation along with small scale industries. Water quality studies on this lake is very scant in literature review. This lake is situated downstream and consequently receives water from lake Bheemasandra and Mallasandra via channels. The upstream lakes in turn face risks of contamination from nearby sewage treatment plant (STP) dedicated to treat the municipal sewage water from Tumakuru city. The STP has capacity of 24.5 million litres per day without any facilities for treating septage which cannot handle the entire load from the city and as a result, both treated and untreated sewage water is directly let into Bheemasandra lake. The water samples were extracted in the month of April (pre-monsoon season) and November (post-monsoon season) of the year 2022 following gran sampling method. The results of the study provide insight on the fate of water quality as it travels downstream and can be helpful for local authorities and decision makers for controlling pollution in these lakes.

The aim of this paper is 1) to analyse physicochemical properties of water samples from Gubbi lake during pre-monsoon and post-monsoon seasons, 2) assess the lake water quality for drinking, irrigation and industrial purposes, 3) subject the water quality data to multivariate statistical techniques and finally 4) to create WQI maps using IDW interpolation method in GIS environment for visualization of water quality results.

Materials and Methods

Study area

Gubbi lake is situated in Gubbi taluk at a distance of about 22 kms from Tumakuru city, in state of Karnataka, India (Figure 1). It is located between

13°19'27.24″N and 13°17'38.41″N latitudes and 76°58'28.91″E and 76°57'34.35″E longitudes spanning over an area of 331.4 hectares and mean elevation of 773 meters above mean sea level. The mean annual precipitation in study area is 743 mm and annual average temperature of 27.08 °C having semi-arid climatic condition.

Sampling method

The application of fishnet tool provided within the framework of ArcGIS software generated equilateral grids which enabled us to achieve uniform and consistent spatial coverage of Gubbi lake to yield 20 strategically positioned sampling points formed at geometric centre of each grid. The points are equidistant from each other separated by a distance of 400 meters. The latitude and longitude coordinates of sampling points were recorded thoroughly and is shown in Table 1. The water samples were systematically collected utilizing a GPS guided system with motorboat and invaluable assistance from local fisherman.

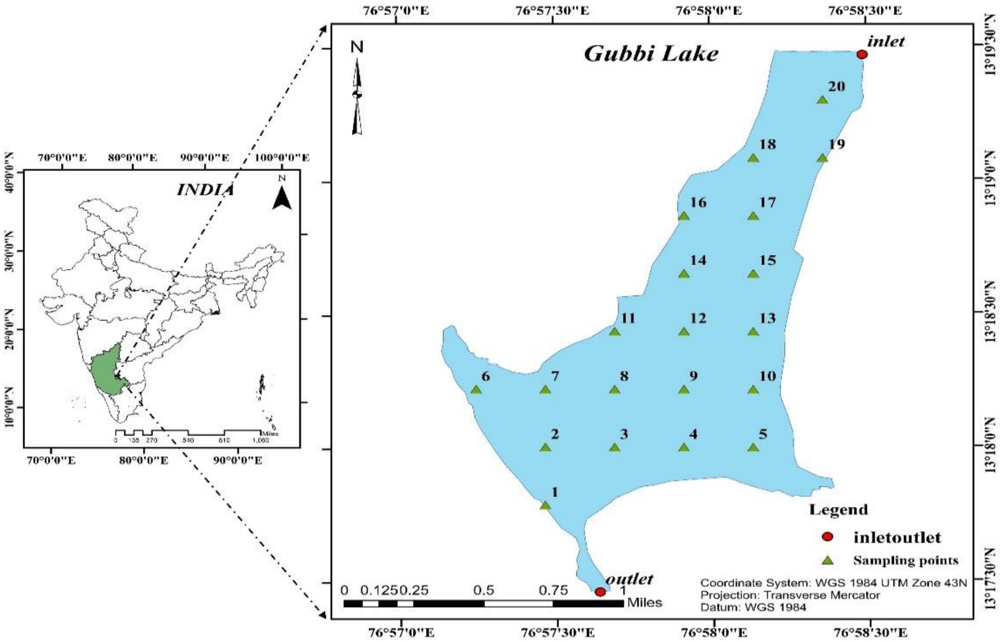

Figure 1. Location map of Gubbi lake

The process of sample extraction involving collection, transportation and storage adhered to the established standards and protocols mentioned in APHA/AWWA/WEF (2012). A portable conductivity multi-parameter apparatus was used to measure the pH and EC in-situ (Hanna HI 9811-5). The dissolved oxygen (DO), biochemical oxygen demand (BOD) and chemical oxygen demand (COD) were determined using electrochemical probe, 5-day BOD test method and open reflux method respectively. Total dissolved solids (TDS) and total suspended solids (TSS) were estimated by gravimetric method, turbidity using nephlo-photometer, ammoniacal nitrogen and nitrate as nitrogen (NO_3^-) by using ion selective electrode method, ortho phosphates as PO_4^{3-} by stannous chloride method. Spectrophotometric

Table 1. GPS co-ordinates of sampling points in Gubbi lake

Sampling points	latitude	longitude	Sampling points	latitude	longitude
1	13.29645	76.957695	11	13.307266	76.961473
2	13.300064	76.957724	12	13.307237	76.965164
3	13.300036	76.961415	13	13.307209	76.968855
4	13.300007	76.965106	14	13.310852	76.965194
5	13.299979	76.968797	15	13.310823	76.968885
6	13.303708	76.954062	16	13.314467	76.965223
7	13.303679	76.957753	17	13.314438	76.968914
8	13.303651	76.961444	18	13.318053	76.968943
9	13.303622	76.965135	19	13.318025	76.972634
10	13.303594	76.968826	20	13.321639	76.972664

method was used to estimate sulphates as SO_4^{2-}, sodium (Na^+) and potassium (K^+) were estimated by flame emission photometric method, calcium (Ca^{2+}), magnesium (Mg^{2+}) and total hardness as $CaCO_3$ by EDTA (Ethylene diamine tetra acetic acid) titrimetric method, total alkalinity as $CaCO_3$ by indicator method, chloride (Cl^-) using argentometric method and fluoride as F^- was estimated using electrochemical probe method. A total of 20 physicochemical parameters were assessed in Gubbi lake water samples.

Water quality indexing approach

Drinking water quality index

For calculation of drinking WQI of Gubbi lake, two preeminent WQI models have been employed entailing the selection of average concentrations of 13 distinct water quality parameters measured at each location. The parameters included are pH, turbidity, BOD, TDS, ammoniacal N, nitrate N, sulphates, calcium, magnesium, total alkalinity, total hardness, chloride and fluoride. It is noteworthy that the benchmark stipulated by Bureau of Indian Standards for drinking water (2012) have been used for the computation of water quality index.

The Canadian Council of Ministers of the Environment Index (CCME-WQI)

CCME WQI is formulated by combining three key factors characterizing the impact of human on water quality (Benkov et al., 2023).

Factor 1: F1 (*Scope*) - It represents those variables, whose objectives remain unachieved.

$$\mathrm{F1} = \left(\frac{\text{Number of failed variables(parameters)}}{\text{Total number of variables}}\right) \times 100 \quad (1)$$

Factor 2: F2 (*Frequency*) - represents the average occurrence and frequency with which tested or observed value exceeded the recommended limits or standards.

$$\mathrm{F2} = \left(\frac{\text{Number of failed tests}}{\text{Total number of tests}}\right) \times 100 \quad (2)$$

Factor 3: F3 (*Amplitude*) - represents the magnitude of disparities or those values whose objectives are not met.

$$\mathrm{F3} = \frac{nse}{(0.01\mathrm{nse} + 0.01)} \quad (3)$$

The *nse* (normalized sum of excursion) variable is expressed in 2 step:

- Calculating Excursion $_i$

For instances in which the test value must not exceed the objective:

$$Excursion\ i = (\text{failed test value } i \ / \text{ Objective } i) - 1 \quad (4)$$

For instances in which the test value must not fall below the objective:

$$Excursion\ i = (\text{Objective } i \ / \text{ failed test value } i) - 1 \quad (5)$$

For instances in which the objective is zero: $Excursion_i = failed\ test\ value_i$

i) Calculating *nse* (normalized sum of excursions)

$$nse = \frac{\sum_{i=1}^{n} \text{Excursion}_i}{Total\ No.\ of\ test} \quad (6)$$

The final CCME water quality index value is formulated using the following equation suggested by (Benkov et al., 2023).

$$\mathrm{CCME-WQI} = 100 - \frac{\sqrt{\mathrm{F1}^2 + \mathrm{F2}^2 + \mathrm{F3}^2}}{1.732} \quad (7)$$

The CCME WQI employs classification of water into five categories based on rating scale as: 'poor' (0 – 44) which indicates water quality is almost always threatened or impaired as conditions usually depart from natural or desirable levels, 'marginal' (45 – 64) that indicates water quality is frequently threatened or impaired as conditions often depart from natural or desirable levels, 'fair' (65 – 79) shows water quality is usually protected but occasionally threatened or impaired as conditions sometimes depart from natural or desirable levels, 'good' (80 – 94) shows water quality is protected with only a minor degree of threat or impairment as conditions rarely depart from natural or desirable levels and 'excellent' (95 – 100) indicates water quality is protected with a virtual absence of threat or impairment as conditions very close to natural or pristine levels exist (Lumb et al., 2011; CCME, 2017).

Irrigation water Quality Index

There are simple indices for assessment of suitability of water for crop irrigation purpose employed in this study for both pre-monsoon and post-monsoon seasons. All the ionic concentrations were quantified in mEq/L. The physical and chemical qualities of surface water parameters, such as pH, EC, TDS, TH, Na, K, Ca, Mg, Cl, SO_4^{2-}, NO_3^- etc. are involved in this evaluation to establish irrigation suitability (Haritash et al., 2016).

Sodium adsorption ratio,

$$SAR = \frac{Na^+}{\sqrt{\frac{Ca^{2+}+Mg^{2+}}{2}}} \tag{8}$$

Sodium percentage,

$$Na\% = \frac{Na^+ + K^+}{Ca^{2+}+Mg^{2+}+Na^+ + K^+} \times 100 \tag{9}$$

Residual sodium carbonate,

$$RSC = (HCO^{3-} + CO_3^{2-}) - (Ca^{2+} + Mg^{2+}) \tag{10}$$

Magnesium Hazard,

$$MH = \frac{Mg^{2+}}{Ca^{2+}+Mg^{2+}} \times 100 \tag{11}$$

Kelly's Index,

$$KI = \frac{Na^+}{Ca^{2+}+Mg^{2+}} \tag{12}$$

Permeability Index,

$$PI = \frac{Na^+ + K^+ + \sqrt{HCO3-}}{Ca^{2+}+Mg^{2+}+Na^+ + K^+} \times 100 \tag{13}$$

Potential Salinity,

$$PS = Cl^- + \frac{1}{2}\, SO_4^{2-} \tag{14}$$

Industrial Water Quality Index

The tendency of water to induce corrosion and scaling is meticulously determined for both pre-monsoon and post-monsoon seasons through application of following indices (Egbueri et al., 2020). All the ions are quantified in mg/l.

Larson-Skold Index,

$$LSI = \frac{Cl^- + SO4^{2-}}{HCO3-} \tag{15}$$

Langelier Index,

$$LI = pH - pHs \tag{16}$$

where pHs = (9.3 + A + B) – (C + D); A = ($\log_{10}$(TDS) – 1) / 10; B = — 13.2 × $\log_{10}$ °C+273) + 34.55; C = $\log_{10}$ (Ca^{2+} as $CaCO_3$) — 0.4; D = $\log_{10}$ (alkalinity as $CaCO_3$)

Aggressive Index,

$$AI = pH + \log10\,(\text{alkalinity} \times \text{Hardness}) \tag{17}$$

Ryznar stability Index,

$$RSI = 2pHs - pH \tag{18}$$

Puckorius scaling Index,

$$PSI = 2pHs - pHeq \tag{19}$$

where pHeq = 1.465 × $\log_{10}$(alkalinity)+4.54 (pHs is the pH at saturation state of $CaCO_3$; pHeq is the pH at equilibrium).

Chloride Sulphate Mass Ratio,

$$CSMR = \frac{Cl^-}{SO4^{2-}} \tag{20}$$

Multivariate Statistical Analysis

All the 20 water quality parameters measured at 20 sampling locations during two seasons were subjected to Principal Component Analysis using IBM SPSS Statistics 26 software. Principal Component Analysis is a pattern recognition technique adopted to elucidate the variance within a large set of interrelated variables. This is met by transmogrifying the variables into smaller set of independent and uncorrelated variables called as principal components (PCs) which are linear combinations of original variables (Shrestha and Kazama, 2007. It enables data interpretation, data reduction and summarization of statistical correlation among constituent variables in water quality context with minimum loss of original information (Rahman et al., 2021).

Water Quality Index map using spatial interpolation method

The inverse distance weighted (IDW) constitutes a dominant deterministic spatial interpolation method that involves determination of cell values through a linearly weighted combination of set of sampling points. It has irreplaceable utility in spatial interpolation of water quality data. To generate a comprehensive WQI map of Gubbi lake, the IDW program in spatial analyst tool within ArcGIS software was employed. This was done by importing CCME WQI values computed at each sampling point and associating them with corresponding GPS coordinates. This method enabled spatial distribution of WQI values across the surface area of entire lake thus providing visual picture of water quality variations.

Results and discussion

Physicochemical properties of water

The descriptive statistical analysis conducted on findings of 20 physicochemical parameters assessed during pre-monsoon and post-monsoon are reported in Table 2.

The pH level is a measure of hydrogen ion activity in water. At Gubbi lake, the pH exhibited a range of 6.77 to 7.28 in pre-monsoon with a calculated mean pH of 6.99. In post-monsoon, the pH value ranged from 7.40 to 7.96 with a recorded mean of 7.79 collectively indicating almost neutral state of lake through both the seasons. These pH levels were within the acceptable limits of Bureau of Indian Standards (2012) which prescribe a range of pH between 6.5 and 8.5. The EC of water during pre-monsoon period displayed a range between 666 to 762.3 µs/cm with a mean value of 719 µs/cm and were within the acceptable benchmark set forth by BIS (2012). During post-monsoon season, it displayed a mean value of 591 µs/cm. The EC of surface waters varies due to factors viz., precipitation levels and geological structure as elucidated by (Ustaoğlu and Tepe, 2019). The elevated levels of EC recorded during pre-monsoon may be attributed to evaporation-induced concentration of ions in water as well as dilution of water following rainfalls. Similar explanations were also furnished by (Gyimah et al., 2021). Low DO levels cause adverse conditions such as onset of anaerobic decomposition of organic matter, fish mortality, development of pungent odour and production of hydrogen sulphide (Rahman et al., 2021). The DO measured at Gubbi lake recorded a mean value of 4.34 mg/l and 5.76 mg/l during pre-monsoon and post-monsoon periods respectively. These values were slightly below the optimal range of 5 to 6 mg/l. The BOD of water is the amount of oxygen required by micro-organisms in order to break down organic matter under aerobic conditions and is usually at elevated levels in polluted waste waters. The BOD values exhibit a mean of 8.5 mg/l and 5.3 mg/l in pre-monsoon and post-monsoon season respectively. BOD levels exceeded the normal range of 5 mg/l in both the seasons although it was slight during post-monsoon season.

Table 2. Descriptive statistics of Gubbi lake during pre-monsoon and post-monsoon season.

Seasons	Pre-monsoon			Post-monsoon		
Parameters	Mean ± sd	Min.	Max.	Mean ± sd	Min.	Max.
pH	6.99 ± 0.04	6.77	7.28	7.79 ± 0.03	7.40	7.96
EC (µs/cm)	719 ± 7.0	666	762.3	591 ± 3.14	569	616
DO (mg/L)	4.34 ± 0.05	3.80	4.70	5.76 ± 0.16	4.40	6.90
BOD (mg/L)	8.50 ± 0.46	6.00	14.5	5.30 ± 0.33	2.74	7.80
COD (mg/L)	96.2 ± 4.66	70.10	132.8	63.5 ± 3.50	39.60	88.32
Turbidity (NTU)	18.7 ± 0.46	16.41	22.6	13.9 ± 0.32	10.70	16.70
TDS (mg/L)	488.7 ± 4.7	452.7	518.4	402 ± 2.13	387.1	418.9
TSS (mg/L)	24.1 ± 0.58	20.00	30.00	17.8 ± 0.49	13.91	21.71
Ammoniacal N NH^{4+} (mg/L)	1.24 ± 0.13	0.680	2.401	0.60 ± 0.04	0.301	0.842
Nitrate NO^{3-} (mg/L)	26.0 ± 1.09	18.92	37.22	17.4 ± 0.30	15.70	19.70
Ortho phosphates PO_4^{3-} (mg/L)	0.33 ± 0.01	0.260	0.411	0.17 ± 0.01	0.071	0.260
Sulphates SO_4^{2-} (mg/L)	31.1 ± 1.84	21.23	47.82	19.4 ± 1.07	8.540	24.32
Sodium Na^+ (mg/L)	71.3 ± 1.24	57.92	80.01	61.0 ± 0.45	58.43	66.82
Potassium K^+ (mg/L)	16.5 ± 0.29	14.29	18.75	8.43 ± 0.10	7.682	9.621
Calcium Ca^{2+} (mg/L)	27.3 ± 0.18	25.60	28.80	21.5 ± 0.23	19.20	23.84
Magnesium Mg^{2+} (mg/L)	15.6 ± 0.11	14.59	16.53	12.1 ± 0.14	10.70	13.52
Total Hardness as $CaCO_3$ (mg/L)	132 ± 0.91	124.0	140.0	103 ± 1.17	92.00	115.2
Total Alkalinity as $CaCO_3$ (mg/L)	204 ± 3.48	176.0	224.0	140 ± 1.29	128.0	152.0
Chloride Cl^- (mg/L)	85.8 ± 1.92	69.00	97.01	68.1 ± 1.84	56.00	88.00
Fluoride F^- (mg/L)	0.34 ± 0.01	0.291	0.390	0.34 ± 0.01	0.278	0.401

The COD in water characterizes both biodegradable and non-biodegradable organic pollutants in water systems and as a result COD values always exceeds BOD values (Ustaoğlu and Tepe, 2019). An increase in COD levels indicates influx of non-biodegradable organic loads from urban sewage and waste water treatment plants and results in reduced DO levels (Rahman et al., 2021). In current study, the average COD was found to be 96.2 mg/l and 63.5 mg/l during pre-monsoon and post-monsoon season respectively. The elevated COD levels can be attributed to influx of polluted waters from upstream lakes. The TDS in water is an important metric involving both dissolved inorganic salts and dissolved organic matter resulting from natural geogenic processes, domestic waste water and industrial discharge as per WHO (2017). As per Bilgin & Konanç (2016), the TDS levels are found to be higher in waters affected by urban and agricultural sources of pollution. The TDS levels exhibited a mean value of 488.7 mg/l and 402 mg/l in pre-monsoon and post-monsoon period respectively. The observed values did not surpass the established limit of 500 mg/l set forth by BIS (2012). The TSS levels recorded at Gubbi lake displayed a mean value of 24.1 mg/l and ranged from 20 to 30 mg/l in pre-monsoon season. During post-monsoon season, it ranged from 13.9 to 21.7 mg/l with a mean of 17.8 mg/l.

The excess of nitrates and phosphates poses a multifaceted threat to aquatic life by promoting growth of harmful algal blooms, depleting oxygen levels and creating dead zones. The major sources of ammonia in water are sewage and agricultural runoff and it renders waste water difficult to be treated. In this investigation, NH^{4+} displayed a recorded mean value of 1.24 mg/l and 0.6 mg/l during pre-monsoon and post-monsoon season respectively. It significantly surpassed the BIS (2012) stipulated threshold of 0.5 mg/l. The nitrate concentration during pre-monsoon period was 26 mg/l and in post-monsoon period, it was registered at 17.4 mg/l suggesting that nitrate levels were within the acceptable limit of 45 mg/l as recommended by BIS (2012). Egbueri (2018) opined that presence of low nitrate levels suggests minimal inputs originating from NPK-rich fertilizers and sewage disposals which might otherwise lead to high nitrate levels in aquatic environment. Phosphate is a prominent nutrient in water vital for growth of aquatic flora and usually ranges from 0.05 to 0.3 mg/l beyond which causes detrimental effects such as eutrophication and depletion of dissolved oxygen. The major sources of PO_4^{3-} ions in water are sewage treatment plants, industrial discharge, agriculture and livestock activities, soil erosion and high dose of fertilizer application leading to higher phosphate levels (Ustaoğlu and Tepe, 2019). PO_4^{3-} concentration in Gubbi lake displayed a mean value of 0.33 and 0.17 mg/l in pre-monsoon and post-monsoon respectively. The sulphate ions exhibited a mean concentration of 31 mg/l during pre-monsoon period while it was recorded at 19.4 mg/l during post-monsoon season. These values were at safe level below acceptable limit of 200 mg/l. Sodium in excess levels result in heightened salinity affecting irrigation and industrial applicability of water causing soil salinization, deterioration of soil quality and reducing uptake of nutrients by plants. The major sources of sodium are salt water intrusion, industrial effluents, weathering of rocks and minerals etc. (Gyimah et al., 2021). Na ion concentration in pre-monsoon period was recorded at 71.3 mg/l and in pre-monsoon period, it had a mean value of 61 mg/l. the K ion concentration in pre-monsoon season recorded a mean value of 16.5 mg/l and in post-monsoon period, the K ion displayed a mean value of 8.43 mg/l. Calcium and magnesium, being abundant among alkali metals, occurs naturally in surface waters (Potasznik and Szynczyk, 2015). The concentration of these alkali metals in surface waters increase periodically over time as they are released from rock formations like gypsum, limestone, dolomite and other gypsiferous substances and are influenced by carbonate balance in water (Galczynska et al., 2013). The mean concentration of Ca ion during pre-monsoon was 27.3 mg/l and in post-monsoon, it was recorded to be 21.5 mg/l. These values were within the BIS (2012) acceptable limit of 75 mg/l in pre-monsoon only. Mg concentration recorded a mean value of 15.6 and 12.1 mg/l through pre-monsoon and post-monsoon season respectively. The Mg ions were within the threshold of 30 mg/l stipulated by BIS (2012). The total alkalinity in pre-monsoon season was registered at an average value of 204 mg/l and during post-monsoon period, it had a mean value of 140 mg/l. Total hardness exhibited an average concentration of 132 mg/l and 103 mg/l over two seasons respectively. The TA exceeded the acceptable limit of 200 mg/l in pre-monsoon period. The Cl ion concentration was within the BIS (2012) acceptable limits of 250 mg/l in Gubbi lake with a mean value of 85.8 and 68.1 mg/l over both the seasons respectively. The fluoride ion concentration did not exceed the BIS (2012) acceptable limits of 1 mg/l with a mean value of 0.34 mg/l and 0.34 mg/l in both the seasons respectively. The average concentrations of cation in Gubbi lake followed the order $Na^+ > Ca^{2+} > Mg^{2+} > K^+ > NH_4^+$ illustrating that sodium was the dominant cation. Conversely, the average anion concentrations followed the order $HCO_3^- > Cl^- > SO_4^{2-} > NO_3^- > F^- > PO_4^{3-}$ rendering bicarbonate ion as the most prevalent among anions.

Water quality index estimation

Evaluation of drinking WQI

Table 3: CCME-WQI of Gubbi lake.

Sample Id	CCME-WQI	class	Sampling points	CCME-WQI	class
1	78.54	Fair	11	75.57	Fair
2	78.20	Fair	12	76.28	Fair
3	78.36	Fair	13	70.19	Fair
4	78.19	Fair	14	71.62	Fair
5	79.05	Fair	15	74.59	Fair
6	81.13	Good	16	67.67	Fair
7	77.56	Fair	17	66.70	Fair
8	76.71	Fair	18	67.33	Fair
9	77.86	Fair	19	67.19	Fair
10	74.02	Fair	20	67.57	Fair
Average = 74.22 (fair)					

In present study, the results obtained from CCME-WQI depicts a comprehensive water quality status by integrating the effects of 13 physicochemical parameters (Table 3). The CCME-WQI ranged from 66.7 at sampling point 17 to 81.13 at sampling point 6 with a recorded average of 74.2. These values are indicative of 'fair' water quality index class falling between 65 and 79 as outlined in CCME-WQI classification scheme (CCME, 2017) with an exception of sampling site 6 classified as 'good'. Thus, the water quality of Gubbi lake is generally protected yet occasionally subjected to threat wherein conditions sometimes depart from that of desirable or natural levels. The spatial distribution map of CCME-WQI is depicted in Figure 2a.

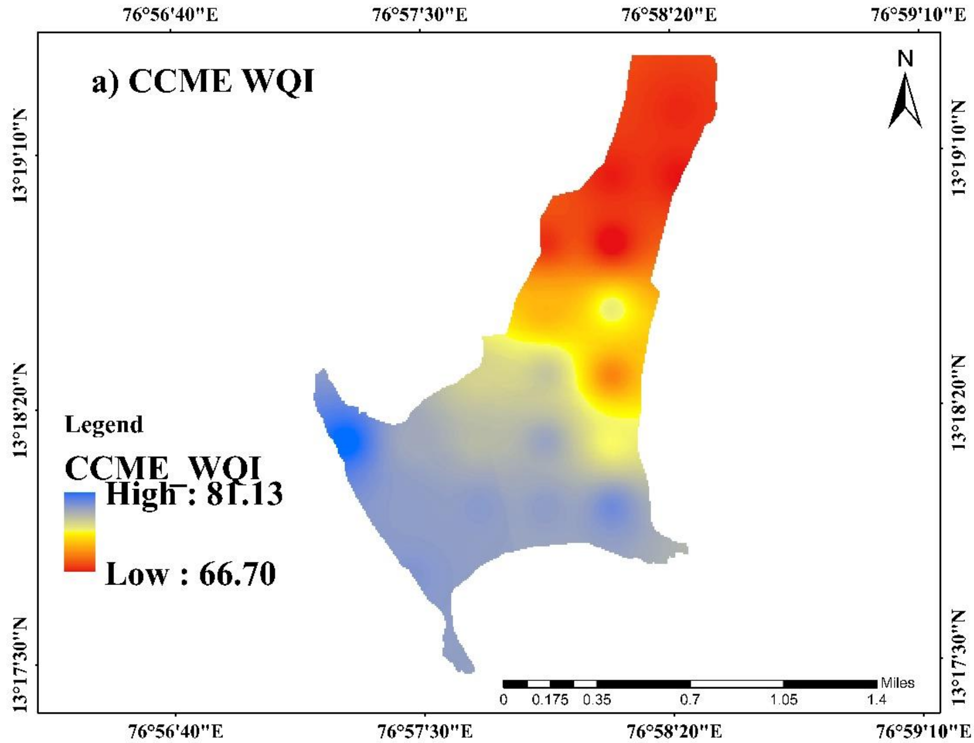

Fig 2: Maps showing spatial interpolation of CCME water quality index

Evaluation of irrigation WQI

The EC of water is a measure of dissolved inorganic salts in water matrix. It holds paramount importance while assessing suitability of water for irrigating crops due to direct impact on osmotic pressure of soil solution and plant's ability to absorb water (Azhari et al., 2023). In the context of this study, the EC of Gubbi lake had mean salinity of 718.7 during pre-monsoon period where 75% of samples were categorized under 'good' and the rest were classified under 'doubtful'. The EC had a mean of 590.8 after monsoon season and all the samples were 'good' for irrigation (Table 4 and 5). This may be attributed to contaminated waters from upstream lakes receiving untreated and treated sewage water from STP nearby Tumakuru city (Figure 3a – 3b).

The sodium adsorption ratio (SAR) or alkali hazard plays a pivotal role in examining the appropriateness of surface waters for irrigation purpose (Srinivasamoorthy et al., 2014). Higher levels of Na ions in water imparts deleterious effects on soil physical properties and causes depletion of soil permeability resulting the formation of alkaline soil. The Ca^{2+} and Mg^{2+} ions balance the adverse effects of Na^{+} ion when present in sufficient quantity in soil and aids in maintaining healthy soil state (El-Amier et al., 2021). In present investigation, SAR displayed a mean value of 2.7 and 2.61 before and after monsoons respectively and thus, all the samples were categorized as 'low' in SAR according to the classification scheme (Table 4 and 5). The spatial interpolation map showing variation of SAR is presented in Figure 3a – 3b.

The sodium ions in water have the propensity to displace calcium and magnesium ions from clay surface. This phenomenon of ion exchange reduces soil permeability and poor internal drainage (Tahmasebi et al., 2018). The Na % of Gubbi lake recorded a mean of 57.1% and 58.2% in pre-monsoon and post-monsoon season respectively (Figure 3e – 3f). The residual sodium carbonate occurs as a result of excess alkalinity concentration in water than alkaline earth metals viz., calcium and magnesium ions (Ravikumar et al., 2011). The RSC in this study exhibited a mean of 0.69 mEq/l before rains and 0.22 mEq/l after the rains. Since, the values were below 1.25 mEq/l in both the periods, the samples fell under 'good' category with respect to irrigation suitability (Figure 3g – 3h).

Table 5. Irrigation Water Quality Indices classification scheme (Azhari et al., 2023)

Index	Range	Remark on quality	No. of samples (%)	
			Pre-monsoon	Post-monsoon
Salinity hazard EC (µs/cm)	100 – 250	Excellent	-	-
	250 – 750	Good	15 (75)	20 (100)
	750 – 2250	Doubtful	5 (25)	-
	> 2250	Unsuitable		
Sodium Adsorption Ratio (SAR)	0–10	Low	20 (100)	20 (100)
	10–18	Medium	-	-
	18–26	High	-	-
	>26	Very high	-	-
Sodium percentage Na%	<20	Excellent	-	-
	20–40	Good	-	-
	40–60	Permissible	20 (100)	17 (85)
	60–80	Doubtful	-	3 (15)
	>80	Unsuitable	-	-
Residual sodium carbonate (RSC)	< 1.25	Good	20 (100)	20 (100)
	1.25–2.50	Doubtful	-	-
	>2.50	Unsuitable	-	-
Magnesium hazard (MH)	<50	Suitable	20 (100)	20 (100)
	<51	Unsuitable		-
Kelly's index (KI)	<1	Suitable	2 (10)	-
	>1	Doubtful	18 (90)	20 (100)
Permeability Index (PI)	>75%	suitable for irrigation	20 (100)	20 (100)
	25–75%	moderately suitable	-	-
	< 25%	unsuitable	-	-
Potential Salinity (PS)	<5	Excellent to Good	20 (100)	20 (100)
	5–10	Good to injurious	-	-
	>10	Injurious to unsatisfactory	-	-

Table 4. Irrigation water quality indices of lake Gubbi over two seasons.

Season	Pre-monsoon								Post-monsoon							
Sample	EC	SAR	Na%	RSC	MH	KI	PI	PS	EC	SAR	Na%	RSC	MH	KI	PI	PS
1	665.8	2.68	57.69	0.46	48.49	1.19	86.42	2.25	576.1	2.60	57.93	0.28	48.13	1.27	89.03	1.94
2	680.4	2.68	56.86	0.25	48.54	1.17	84.64	2.31	579.8	2.66	58.93	0.23	48.05	1.33	89.62	1.83
3	677.1	2.68	56.67	0.31	48.54	1.17	84.89	2.24	585.3	2.77	60.40	0.25	47.97	1.41	90.76	2.05
4	714.8	2.83	59.30	0.60	48.44	1.27	88.13	2.44	582.9	2.62	58.63	0.17	48.05	1.31	89.08	1.81
5	679.4	2.94	59.39	0.39	48.49	1.30	86.66	2.55	569.3	2.55	57.49	0.02	48.13	1.25	87.12	1.89
6	692.5	2.75	57.07	0.49	48.58	1.18	85.38	2.66	574.2	2.71	60.46	0.39	47.88	1.42	92.57	1.89
7	713.7	2.75	57.51	0.64	48.54	1.20	86.67	2.78	586.8	2.62	58.60	0.23	48.05	1.31	89.53	2.02
8	723.4	2.13	51.55	0.55	48.63	0.90	83.22	3.22	588.6	2.61	58.06	0.22	48.13	1.28	88.63	2.28
9	713.8	2.68	56.64	0.57	48.54	1.17	86.10	2.91	580.2	2.65	58.91	0.23	48.05	1.32	89.61	2.23
10	695.4	2.29	52.91	0.56	48.58	0.98	84.28	2.47	575.9	2.62	58.34	0.25	48.10	1.30	89.18	2.19
11	700.8	2.66	57.00	0.77	48.54	1.16	87.10	2.69	596.7	2.63	58.14	0.30	48.12	1.29	89.33	1.94
12	705.6	2.49	56.22	0.92	48.49	1.10	88.13	2.77	580.5	2.55	58.01	0.24	48.05	1.28	89.51	2.49
13	761.8	2.46	55.04	0.82	48.58	1.06	86.17	3.23	588.0	2.54	57.37	0.21	48.14	1.24	88.32	2.66
14	742.7	2.93	58.96	0.97	48.54	1.28	88.51	3.11	606.2	2.53	57.35	0.22	48.13	1.24	88.44	2.17
15	735.2	2.89	57.78	0.68	48.63	1.22	85.91	2.77	602.7	2.46	55.79	0.14	48.26	1.17	86.36	2.22
16	745.4	3.03	59.43	0.97	48.54	1.32	88.64	2.67	608.2	2.41	54.89	0.06	48.32	1.12	84.99	2.00
17	750.5	2.79	58.45	1.05	48.49	1.24	89.30	2.71	606.7	2.48	56.08	0.22	48.24	1.18	87.09	2.02
18	758.8	2.75	57.58	0.95	48.58	1.18	87.49	2.90	602.4	2.73	58.82	0.15	48.19	1.32	87.94	2.16
19	755.4	2.86	58.44	0.97	48.54	1.24	88.36	3.01	610.0	2.87	60.47	0.44	48.11	1.41	90.84	2.34
20	762.3	2.63	56.46	0.90	48.54	1.15	87.52	3.14	616.0	2.65	58.39	0.24	48.17	1.29	88.57	2.27
Min.	665.8	2.13	51.55	0.25	48.44	0.90	83.22	2.24	569.3	2.41	54.89	0.02	47.88	1.12	84.99	1.81
Max.	762.3	3.03	59.43	1.05	48.63	1.32	89.30	3.23	616.0	2.87	60.47	0.44	48.32	1.42	92.57	2.66
Average	718.7	2.70	57.05	0.69	48.54	1.17	86.68	2.74	590.8	2.61	58.15	0.22	48.11	1.29	88.83	2.12

EC – Electrical Conductivity, SAR - Sodium Absorption Ratio, Na% - Sodium Percentage, RSC – Residual Sodium Carbonate, MH – Magnesium Hazard, KI – Kelly's Index, PI - Permeability Index, PS – Potential Salinity

The MH in this study were below 50 % in all the samples over both the seasons (Figure 3i – 3j) and hence, recommended for irrigation purpose without any cause of concern. Before monsoon rains, the KI recorded a mean of 1.17 and after monsoons, it displayed a mean value of 1.29 (Figure 3k – 3l). These values categorized 90% of samples as unsuitable for irrigation during pre-monsoon period whereas during post-monsoon season, all the samples were rendered unsuitable. Prolonged exposure to heightened concentrations of Ca, Mg, Na and HCO_3^- ions in irrigation water can impact soil permeability (Ravikumar et al., 2011; Egbueri et al., 2021). Doneen (1964), first introduced permeability index for examination of irrigation water suitability. During pre-monsoon period, the average PI value was computed to be 86.68 % and after monsoon rains, the Gubbi lake water samples displayed a mean of 88.8 % (Figure 3m – 3n). These values suggested that the water was suitable for irrigation over both the seasons. The PS refers to the quantity of salts that build up in soil as it dissolves constantly due to prolonged irrigation of soil. The PS values in pre-monsoon and post-monsoon season categorized all samples under 'excellent to good' class for irrigation (Figure 3o – 3p).

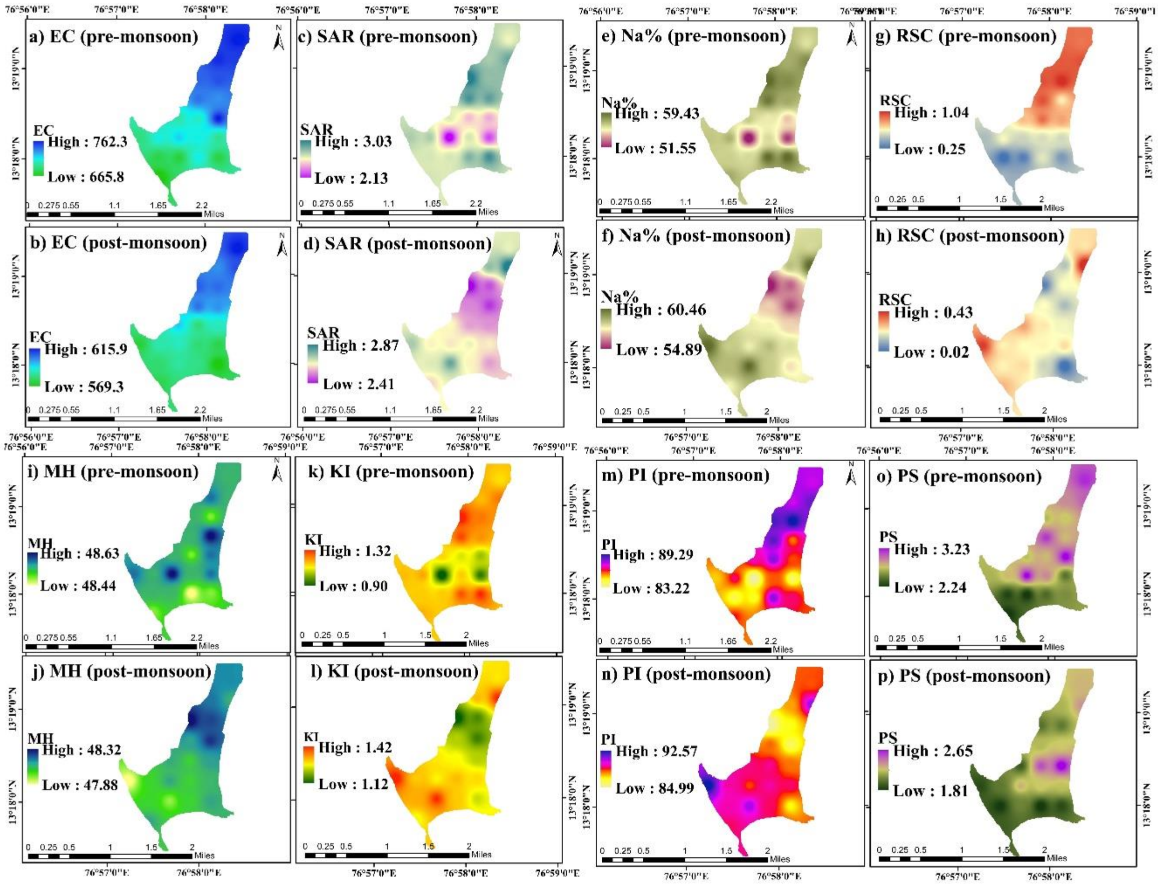

Figure 3. Maps showing spatial interpolation of irrigation WQIs during pre-monsoon and post-monsoon season

Evaluation of industrial WQI

Larson and Skold (1958) developed the LSI index to quantify the ratio of Cl^- and SO_4^{2-} ion concentration to CO_3^{2-} and HCO_3^- ions concentration in water. The LSI values during pre-monsoon season ranged from 0.5 to 0.7 with an average of 0.57. During post-monsoon time, it recorded a range between 0.54 to 0.75 with a mean of 0.63 in waters of Gubbi lake (Table 6) (Figure 4a – 4b). These values indicate that the water exhibits scaling tendency during both the seasons as per the classification scheme (Table 7). The LI is widely used by water operators to assess internal corrosion and scaling propensity of water (Ahmed et al., 2021). It portrays the condition where water shows equilibrium condition with $CaCO_3$. The LI formula determines the propensity of calcium carbonate to form precipitation or to dissolve under varying circumstances (Uddin et al., 2020). The LI displayed a mean of negative 0.62 and negative 0.09 during pre-monsoon and post-monsoon season respectively (Figure 4c – 4d). Since all the samples had negative values, the water was not saturated and exhibited corroding tendency in pre-monsoon period. Whereas during post-monsoon period, 12 samples exhibited corroding tendency without any saturation and 8 samples were supersaturated having scaling tendency. Aggressive index (AI) is usually used as an alternative tool for Langelier index (LI) due to its simpler calculations without demanding the TDS as well as temperature values. However, it is considered less accurate compared to LI and is a general indicator of corrosiveness of water. It involves pH, calcium hardness and total alkalinity for computation (Ahmed et al., 2021).

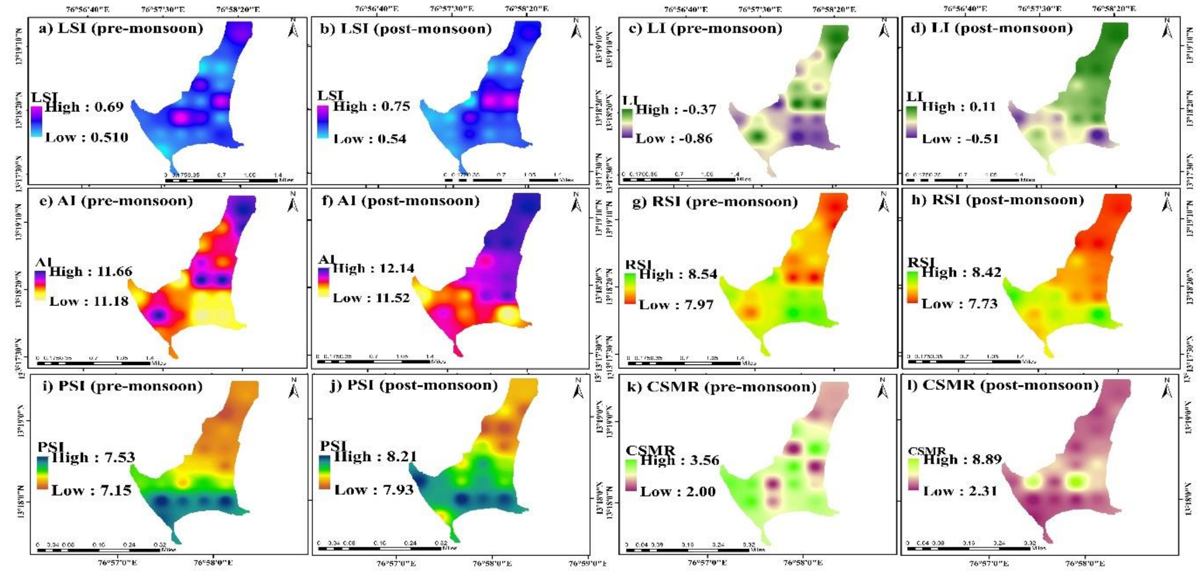

Fig 4: Maps showing spatial interpolation of industrial WQIs during pre-monsoon and post-monsoon season

The AI values were found ranging from 11.18 and 11.67 with a mean of 11.42 during pre-monsoon time. All 20 samples had AI values between 10 and 12 and thus exhibited moderate corrosiveness before monsoons. After the monsoons, the AI ranged from 11.52 to 12.14 with an average value of 11.94 indicating 11 samples possessed moderate corrosiveness and 9 samples had scaling and non-aggressive tendency (Figure 4e – 4f). The RSI values were found between 7.97 and 8.55 with a mean of 8.24 during pre-monsoon season. 19 samples had RSI values between 6.2 and 6.8 exhibiting no scaling or corrosive tendency except sample 4 which had rigorous scaling tendency before monsoons. After the rainfall, the RSI ranged from 7.73 to 8.42 with an average value of 7.97 RSI (Figure 4g – 4h). All 20 samples had corrosive propensity. A reaction occurs where water with higher Ca^{2+} ions and comparatively lower CO_3^{2-}, accounts in swift reduction of pH by consuming CO_3^{2-} to form $CaCO_3$. This situation implies the low buffering capacity where water lacks enough CO_3^{2-} ions to counteract the swift drop in pH. Hence, the PSI quantifies the buffering capacity and precipitation forming potential of water in order to achieve the state of equilibrium (Uddin et al., 2020). In this study, the PSI values had a mean of 7.32 before monsoons and 8.07 after monsoons (Figure 4i – 4j). These values suggested all the water samples to possess significant corrosive tendency over both the seasons. The CSMR, as the name suggests, is the proportion of chloride and sulphate ion concentration in water to assess the galvanic corrosion potential of water. Its value registered a mean of 2.88 and 3.86 before and after monsoon season respectively. These values categorized all the water samples as to possess galvanic corrosion potential (Figure 4k – 4l).

Principal component analysis

In this experiment, the PCA was executed on 20 water quality parameters using varimax rotation over both the seasons. The significance of PC is measured by its eigen value, and those PCs with eigen value greater than 1 were extracted (Shrestha and Kazama, 2007). As per Liu et al. (2003), the factor loadings were classified based on loading values as 'strong' (>0.75), 'moderate' (0.5 to 0.75) and 'weak' (0.3 to 0.5) loadings.

Table 6: Industrial water quality indices of Gubbi lake over two seasons.

Season	Pre-monsoon						Post-monsoon					
Sample	LSI	LI	AI	RSI	PSI	CSMR	LSI	LI	AI	RSI	PSI	CSMR
1	0.51	-0.66	11.38	8.33	7.49	3.02	0.58	-0.11	11.93	7.97	8.02	2.52
2	0.54	-0.40	11.65	8.08	7.53	3.49	0.59	-0.06	11.97	7.96	8.14	2.31
3	0.54	-0.61	11.44	8.28	7.49	2.41	0.66	-0.25	11.78	8.18	8.21	2.69
4	0.55	-0.87	11.18	8.55	7.49	2.98	0.59	-0.16	11.87	8.08	8.18	2.51
5	0.59	-0.80	11.24	8.48	7.52	3.19	0.61	-0.51	11.52	8.42	8.19	3.21
6	0.56	-0.75	11.30	8.37	7.34	3.39	0.58	-0.41	11.62	8.35	8.20	3.16
7	0.58	-0.59	11.46	8.21	7.34	3.40	0.57	-0.24	11.79	8.14	8.14	7.09
8	0.70	-0.67	11.38	8.27	7.26	2.10	0.69	-0.29	11.74	8.16	8.06	2.96
9	0.62	-0.79	11.25	8.43	7.37	3.37	0.62	0.01	12.04	7.89	8.14	8.90
10	0.53	-0.78	11.26	8.39	7.31	2.69	0.62	0.06	12.10	7.82	8.07	4.83
11	0.54	-0.84	11.21	8.45	7.28	3.01	0.54	-0.04	11.99	7.91	8.03	4.86
12	0.54	-0.37	11.67	7.99	7.28	3.52	0.75	-0.04	11.99	7.94	8.14	3.55
13	0.67	-0.39	11.66	7.97	7.20	2.03	0.75	0.03	12.06	7.84	8.06	5.10
14	0.63	-0.51	11.54	8.09	7.20	2.00	0.66	-0.14	11.89	8.02	8.06	2.86
15	0.54	-0.67	11.38	8.24	7.21	3.56	0.63	-0.02	12.01	7.86	7.96	3.95
16	0.51	-0.71	11.34	8.29	7.20	3.25	0.57	0.08	12.12	7.74	7.93	3.48
17	0.52	-0.59	11.46	8.19	7.23	2.83	0.57	0.10	12.13	7.73	7.93	3.13
18	0.57	-0.68	11.37	8.24	7.15	2.35	0.66	0.07	12.11	7.79	8.04	2.87
19	0.59	-0.41	11.64	7.99	7.20	2.49	0.62	0.03	12.06	7.82	7.95	4.01
20	0.63	-0.39	11.66	7.99	7.23	2.51	0.66	0.11	12.14	7.75	8.01	3.19
Min.	0.51	-0.87	11.18	7.97	7.15	2.00	0.54	-0.51	11.52	7.73	7.93	2.31
Max.	0.70	-0.37	11.67	8.55	7.53	3.56	0.75	0.11	12.14	8.42	8.21	8.90
Average	0.57	-0.62	11.42	8.24	7.32	2.88	0.63	-0.09	11.94	7.97	8.07	3.86

LSI - Larson-Skold Index, LI - Langelier Index, AI – Aggressive Index, RSI - Ryznar Stability Index, PSI - Puckorious Scaling Index, CSMR - Chloride Sulphate Mass Ratio

Table 7. Industrial Water Quality Indices Classification Scheme (Egbueri et al., 2021)

Index	Range	Remark on quality	No. of samples (%)	
			Pre-monsoon	Post-monsoon
Larson-Skold Index (LSI)	< 0.8	Water has scaling tendency	20 (100)	20 (100)
	0.8 – 1.2	Higher corrosion rates can be obtained	-	-
	> 1.2	High rates of localized corrosion are expected	-	-
Langelier Index (LI)	< 0	Water is not saturated and has corroding tendency	20 (100)	12 (60)
	= 0	Water is saturated and has no scaling tendency	-	-
	> 0	Water is supersaturated and has scaling tendency	-	8 (40)
Aggressive Index (AI)	< 10	Water is severely corrosive (highly aggressive)	-	-
	10 - 12	Water is moderately corrosive	20 (100)	11 (55)
	> 12	Water has scaling tendency and has non-aggressive tendency	-	9 (45)
Ryznar Stability Index (RSI)	< 5.5	Water has rigorous scaling tendency	-	-
	5.5 – 6.2	Water has scaling tendency	-	-
	6.2 – 6.8	Water is balanced and has no scaling or corrosive tendencies	-	-
	6.8 – 8.5	Water has corrosive tendency	19 (95)	20 (100)
	> 8.5	Water has rigorous corrosive tendency	1 (5)	-
Puckorious Scaling Index (PSI)	< 6	Water has scaling tendency	-	-
	6 -7	Water has little scaling and corrosive tendencies	-	-
	> 7	Water has significant corrosive tendency	20 (100)	20 (100)
Chloride Sulphate Mass Ratio (CSMR)	< 0.5	Water has no galvanic corrosion potential	-	-
	> 0.5	Water with galvanic corrosion potential	20 (100)	20 (100)

PCA performed on pre-monsoon season dataset resulted in 6 components explaining 87.85 % of variance in water quality data (Table 9). The scree plot obtained from PCA during pre-monsoon is shown in Figure 5a. The KMO (Kaiser–Meyer–Olkin) value of 0.709 (> 0.6) and Bartlett's Sphericity test of significance with (p value less than 0.05) indicated the suitability of dataset for conducting PCA. PC1 explicated 29.12 % of total variance having strong loadings of NH_4^+, COD, BOD, TA, TDS and EC representing organic source of pollution that can be ascribed to domestic discharge. Soon after the rains, the lithological influence may be subdued by rainfall-induced dilution uncovering the effects of organic pollutants. PC2 has strong loadings of inorganic species Ca^{2+}, TH and Mg^{2+} depicting natural lithological process. PC3 displays 14.2 % of total variance with strong (turbidity and TSS) and moderate (K^+) loadings explaining possible sources of agricultural runoff from the vicinity. PC4, PC5 and PC6 explained 11.2%, 8.4% and 8.08% of total variance respectively. The effects of sulphates, nitrates and phosphates were comparatively low which may be ascribed to dilution after rainfall.The PCA during post-monsoon season produced 6 components explaining 89.80 % of variance responsible for water quality in Gubbi lake (Table 9). The scree plot obtained from PCA during post-monsoon is shown in Figure 5b. The PC1 explicated 27.8 % of total variance with strong loadings of Ca^{2+}, TH, Mg^{2+}, TH, F^-, EC and TDS. This illustrated the influence of inorganic parameters due to natural lithological process such as weathering of rocks over long periods of time. Further, the Ca and Mg concentration impacted EC more than Na or K ions (Galgundi and Shetty, 2018). PC2 elucidates 21.3 % of total variance with strong loadings of COD, NH_4^+, BOD and DO which are oxygen-demanding pollutants (Gyimah et al., 2021). PC2 explains the organic pollution mainly from domestic sewage waters from upstream lakes and agricultural runoff. Further, PC3 display strong loadings of sodium and potassium attributed to polluted waters from Mallasandra and Bheemasandra lakes along with agricultural fertilizers reaching the lake waters. PC4 had strong loadings of TSS and turbidity showing organic pollution. PC5 had strong and moderate loadings of sulphates and chloride respectively. PC6 explained nitrate contamination explaining 6.7 % of total variance.

Table 8. Rotated factor loadings of principal component analysis over two seasons.

Pre-monsoon							Post-monsoon						
	components							components					
Variables	1	2	3	4	5	6	Variables	1	2	3	4	5	6
Ca^{2+}	0.970	0.006	-0.098	0.016	-0.080	0.013	NH_4^+	0.938	0.213	-0.077	-0.026	0.022	0.140
Mg^{2+}	0.932	0.035	-0.215	0.033	-0.104	0.108	COD	0.938	0.213	-0.077	-0.026	0.022	0.140
TH	0.927	-0.135	-0.102	-0.193	-0.059	-0.085	BOD	0.938	0.213	-0.077	-0.026	0.022	0.140
F^-	0.898	0.217	0.034	0.153	0.113	-0.027	TA	0.757	0.115	0.245	0.365	0.068	0.104
EC	0.878	0.121	0.085	0.401	-0.070	-0.041	TDS	0.754	0.120	0.584	0.019	0.085	-0.128
TDS	0.878	0.121	0.085	0.401	-0.070	-0.041	EC	0.754	0.120	0.584	0.019	0.085	-0.128
TA	0.085	0.977	0.006	0.158	0.018	0.071	Ca^{2+}	0.636	0.162	0.315	0.251	0.264	-0.402
COD	0.085	0.977	0.006	0.158	0.018	0.071	TH	0.094	0.973	0.134	0.069	-0.058	-0.034
NH_4^+	0.085	0.977	0.006	0.158	0.018	0.071	Mg^{2+}	0.158	0.960	0.155	0.070	-0.034	-0.016
BOD	-0.109	0.029	0.945	0.092	-0.043	-0.141	Turbidity	0.200	0.940	0.162	0.064	-0.036	-0.014
DO	-0.205	0.067	0.924	0.154	-0.030	0.016	TSS	-0.372	-0.868	-0.167	-0.044	-0.135	-0.144
K^+	0.253	-0.132	0.736	0.037	0.417	-0.075	K^+	0.147	0.436	0.761	0.147	0.033	0.210
Na^+	-0.050	-0.219	-0.136	-0.899	-0.132	-0.060	F^-	-0.091	0.291	0.755	0.289	0.031	-0.115
TSS	0.439	0.287	0.309	0.647	-0.051	-0.177	SO_4^{2-}	-0.015	0.141	0.077	0.947	0.071	0.010
Turbidity	0.541	0.299	0.004	0.631	0.142	-0.147	Cl^-	0.095	0.044	0.180	0.940	-0.066	-0.075
SO_4^{2-}	0.017	-0.027	-0.244	0.039	-0.830	0.166	NO_3^-	0.140	-0.089	0.228	0.392	-0.766	0.169
Cl^-	-0.242	0.060	-0.155	0.216	0.736	0.103	DO	0.154	-0.256	0.213	0.264	0.746	0.251
PO_4^{3-}	0.117	-0.111	-0.148	0.203	0.276	-0.805	pH	0.564	-0.025	0.445	-0.007	0.574	0.205
pH	-0.021	0.191	-0.336	0.150	0.106	0.758	PO_4^{3-}	0.420	0.419	0.138	0.337	0.522	0.012
NO_3^-	0.326	-0.314	-0.382	-0.089	0.332	0.485	Na^+	0.180	0.059	0.011	-0.029	0.091	0.929
Eigenvalue	5.823	3.356	2.848	2.236	1.689	1.616	Eigenvalue	5.577	4.260	2.460	2.438	1.878	1.347
Variance %	29.12	16.78	14.24	11.18	8.446	8.082	Variance %	27.88	21.29	12.29	12.19	9.392	6.735
Cumulative %	29.12	45.90	60.14	71.32	79.77	87.85	Cumulative %	27.88	49.18	61.48	73.67	83.06	89.80

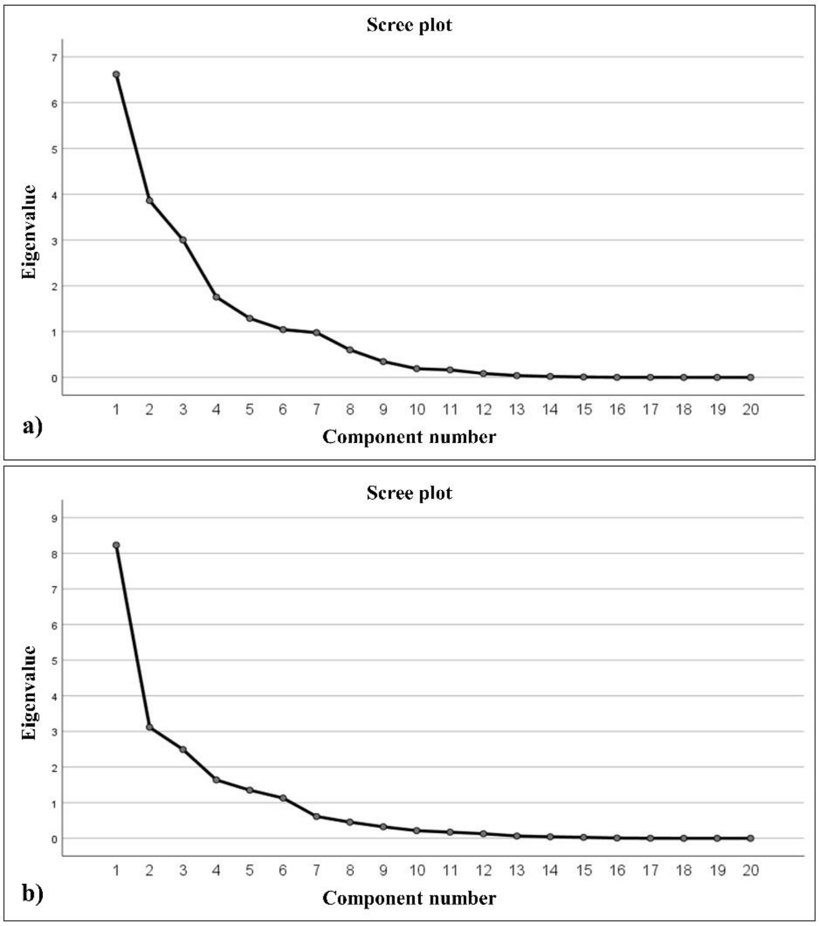

Figure 5. Scree plots of PCA a) pre-monsoon b) post-monsoon

Conclusion

The burgeoning economy of Tumakuru city due to urbanization and industrialization have raised significant environmental concerns regarding the quality of the lakes in the vicinity due to release of untreated sewage from urban settlements. This study aims to investigate the water quality of Gubbi lake by using WQI models, multivariate statistical technique and GIS technology to address these water quality issues. The study revealed that BOD and ammonia levels in water surpassed the Bureau of Indian Standards (BIS) acceptable limits during pre-monsoon and post-monsoon seasons whereas, total alkalinity exceeded only in pre-monsoon season. The CCME-WQI classified the water as 'fair' class elucidating that Gubbi lake water is not fit for direct consumption. All the irrigation WQIs except Kelly's index indicated suitability of majority of water samples for irrigation. The industrial WQIs viz., LI, AI, RSI, PSI and CSMR indicated that majority of water samples exhibited corroding propensity except LSI that displayed corrosion potential. PCA significantly reduced the dimensionality of water quality analysis by formation of 6 PCs each for pre-monsoon and post-monsoon seasons explaining 87.85 % and 89.80 % of total variance respectively. The 6 PCs specified the possible sources of pollution from lithological and anthropological activities including domestic sewage waters, agricultural runoff and weathering of rocks and minerals in Gubbi lake. Further, the utilization of GIS technology facilitated better visualization of WQI results to comprehend spatial and temporal variations in lake water. The findings of this study call upon swift and prompt action by local authorities to implement holistic solutions to mitigate contamination of upstream lakes that carry the polluted waters to Gubbi lake. The extent of pollution is predominant in upstream lakes such as Bheemasandra and Mallasandra lakes and it gradually decreases as the water travels downstream. In addition, this study suggests that future research should include an analysis of heavy metals, pesticides and sediment contamination in Gubbi lake as future line of work.

Author contribution

S K Dhanush: Conceptualization, Methodology, Formal analysis, Investigation, Writing - Original Draft, Writing - Review & Editing. **M. M. Murthy:** Formal analysis, Resources, Supervision, Writing - Review & Editing. **A. Sathish:** Software, Visualization, Writing - Review & Editing. **R. Verma:** Investigation, Visualization, Writing - Review & Editing.

Acknowledgements

The authors are greatly thankful to Sarvath, Darshan, Jeevan and Mamatha (Water testing laboratory) for handling and transporting water samples. Further, we thank Vinay and Nithin, Department of Soil Science and Agricultural Chemistry, University of Agricultural Sciences, Bangalore for their invaluable tips in remote sensing aspects.

Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

References

Abdulsalam, A., Ramli, M. F., Jamil, N. R., Ashaari, Z. H., & Umar, D. U. A. (2022). Hydrochemical characteristics and identification of groundwater pollution sources in tropical savanna. *Environmental Science and Pollution Research*, *29*(25), 37384-37398. https://doi.org/10.1007/s11356-022-18552-0

Ahmed, S., Sultan, M. W., Alam, M., Hussain, A., Qureshi, F., & Khurshid, S. (2021). Evaluation of corrosive behaviour and scaling potential of shallow water aquifer using corrosion indices and geospatial approaches in regions of the Yamuna river basin. *Journal of King Saud University-Science*, *33*(1), 101237. https://doi.org/10.1016/j.jksus.2020.101237

Alexakis, D. E. (2022). Applying Factor Analysis and the CCME Water Quality Index for Assessing Groundwater Quality of an Aegean Island (Rhodes, Greece). *Geosciences*, *12*(10), 384.

APHA/AWWA/WEF (2012). Standard methods for the examination of water and wastewater. Standard methods. (541) https://doi.org/ISBN9780875532356

Azhari, H. E., Cherif, E. K., Sarti, O., Azzirgue, E. M., Dakak, H., Yachou, H., ... & Salmoun, F. (2023). Assessment of Surface Water Quality Using the Water Quality Index (IWQ), Multivariate Statistical Analysis (MSA) and Geographic Information System (GIS) in Oued Laou Mediterranean Watershed, Morocco. *Water*, *15*(1), 130. https://doi.org/10.3390/w15010130

Benkov, I., Varbanov, M., Venelinov, T., & Tsakovski, S. (2023). Principal Component Analysis and the Water Quality Index—A Powerful Tool for Surface Water Quality Assessment: A Case Study on Struma River Catchment, Bulgaria. *Water*, *15*(10), 1961. https://doi.org/10.3390/w15101961

Bilgin, A., & Konanç, M. U. (2016). Evaluation of surface water quality and heavy metal pollution of Coruh River Basin (Turkey) by multivariate statistical methods. *Environmental Earth Sciences*, *75*, 1-18. https://doi.org/10.1007/s12665-016-5821-0

Brown, R. M., McClelland, N. I., Deininger, R. A., & Tozer, R. G. (1970). A water quality index-do we dare. *Water and sewage works*, *117*(10).

Bureau of Indian Standards (2012) Specification for drinking water. IS:10500, New Delhi, India

Burek, P. et al. Water Futures and Solution: Fast Track Initiative (Final Report). IIASA Working Paper (International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria, 2016).

Canadian Council of Ministers of the Environment (C.C.M.E.), 2017. Canadian Water Quality Guidelines for the Protection of Aquatic Life, Canadian Water Quality Guideline for the Protection.

Census of India, 2011. Houselisting and housing data: Households by availability of type of latrine facility. https://www.censusindia.gov.in/DigitalLibrary/TablesSeries2011.aspx

Doneen, L. D., 1964, Notes on water quality in agriculture. Water Science and Engineering, University of California, Davis, CA, USA.

Egbueri, J. C. (2018). Assessment of the quality of groundwaters proximal to dumpsites in Awka and Nnewi metropolises: a comparative approach. *International journal of energy and water resources*, *2*(1-4), 33-48. https://doi.org/10.1007/s42108-018-0004-1

Egbueri, J. C., Ezugwu, C. K., Unigwe, C. O., Onwuka, O. S., Onyemesili, O. C., & Mgbenu, C. N. (2020). Multidimensional analysis of the contamination status, corrosivity and hydrogeochemistry of groundwater from parts of the Anambra Basin, Nigeria. *Analytical Letters*, *54*(13), 2126-2156. https://doi.org/10.1080/00032719.2020.1843049

Egbueri, J. C., Mgbenu, C. N., Digwo, D. C., & Nnyigide, C. S. (2021). A multi-criteria water quality evaluation for human consumption, irrigation and industrial purposes in Umunya area, southeastern Nigeria. *International Journal of Environmental Analytical Chemistry*, *103*(14), 3351-3375. https://doi.org/10.1080/03067319.2021.1907360

El-Amier, Y. A., Kotb, W. K., Bonanomi, G., Fakhry, H., Marraiki, N. A., & Abd-ElGawad, A. M. (2021). Hydrochemical assessment of the irrigation water quality of the El-Salam canal, Egypt. *Water*, *13*(17), 2428. https://doi.org/10.3390/w13172428

Elsayed, S., Hussein, H., Moghanm, F. S., Khedher, K. M., Eid, E. M., & Gad, M. (2020). Application of irrigation water quality indices and multivariate statistical techniques for surface water quality assessments in the Northern Nile Delta, Egypt. *Water*, *12*(12), 3300. https://doi.org/10.3390/w12123300

Gałczyńska, M., Gamrat, R., Burczyk, P., Horak, A., & Kot, M. (2013). The influence of human impact and water surface stability on the concentration of selected mineral macroelements in mid-field ponds. *Woda Środowisko Obszary Wiejskie*, *13*(43), 41-54. https://www.cabdirect.org/cabdirect/abstract/20143059355

Gulgundi M S and Shetty A, 2018, Groundwater quality assessment of urban Bengaluru using multivariate statistical techniques, Applied Water Science (2018) 8:43 https://doi.org/10.1007/s13201-018-0684-z

Gyimah, R. A. A., Gyamfi, C., Anornu, G. K., Karikari, A. Y., & Tsyawo, F. W. (2020). Multivariate statistical analysis of water quality of the Densu River, Ghana. *International Journal of River Basin Management*, *19*(2), 189-199. https://doi.org/10.1080/15715124.2020.1803337

Haritash, A. K., Gaur, S., and Garg, S., 2016, Assessment of water quality and suitability analysis of River Ganga in Rishikesh, India. Appl. Water Sci., 6: 383–392. https://doi.org/10.1007/s13201-014-0235-1

He, C., Liu, Z., Wu, J., Pan, X., Fang, Z., Li, J. and Bryan, B. A. 2021. Future global urban water scarcity and potential solutions. Nature Communications. Vol. 12, Article 4667. http://doi.org/10.1038/s41467-021-25026-3

Horton, R. K. (1965). An index number system for rating water quality. *J Water Pollut Control Fed*, *37*(3), 300-306.

Larson, T. E., & Skold, R. V. (1958). Laboratory studies relating mineral water quality of water on corrosion of steel and cast iron. Corrosion, 14, 285–288.

Lumb, A.; Sharma, T.C.; Bibeault, J.F. A review of genesis and evolution of water quality index (WQI) and some future directions. Water Qual. Expo. Health 2011, 3, 11–24.

Ma, X., Wang, L., Yang, H., Li, N., & Gong, C. (2020). Spatiotemporal analysis of water quality using multivariate statistical techniques and the water quality identification index for the Qinhuai River Basin, East China. *Water*, *12*(10), 2764. https://doi.org/10.3390/w12102764

Mir, R. A., & Gani, K. M. (2019). Water quality evaluation of the upper stretch of the river Jhelum using multivariate statistical techniques. *Arabian Journal of Geosciences*, *12*, 1-19. https://doi.org/10.1007/s12517-019-4578-7

Potasznik, A., & Szymczyk, S. (2015). Magnesium and calcium concentrations in the surface water and bottom deposits of a river-lake system. *Journal of Elementology*, *20*(3). http://dx.doi.org/10.5601/jelem.2015.20.1.788

Rahman, K., Barua, S., & Imran, H. M. (2021). Assessment of water quality and apportionment of pollution sources of an urban lake using multivariate statistical analysis. *Cleaner Engineering and Technology*, *5*, 100309. https://doi.org/10.1016/j.clet.2021.100309

Ravikumar, P., Somashekar, R. K., & Angami, M. (2011). Hydrochemistry and evaluation of groundwater suitability for irrigation and drinking purposes in the Markandeya River basin, Belgaum District, Karnataka State, India. *Environmental monitoring and assessment*, *173*, 459-487. https://doi.org/10.1007/s10661-010-1399-2

Shil, S., Singh, U. K., & Mehta, P. (2019). Water quality assessment of a tropical river using water quality index (WQI), multivariate statistical techniques and GIS. *Applied water science*, *9*, 1-21. https://doi.org/10.1007/s13201-019-1045-2

Shivayogimath, C. B., Kalburgi, P. B, DeshannavaR, U. B., AND Virupakshaiah, D. B. M., 2012, Water quality evaluation of River Ghataprabha, India. Research Journal of Environment Sciences., Vol. 1(1) p. 12–18.

Shrestha, S., & Kazama, F. (2007). Assessment of surface water quality using multivariate statistical techniques: A case study of the Fuji river basin, Japan. *Environmental Modelling & Software*, *22*(4), 464-475. https://doi.org/10.1016/j.envsoft.2006.02.001

Srinivasamoorthy, K., Gopinath, M., Chidambaram, S., Vasanthavigar, M., & Sarma, V. S. (2014). Hydrochemical characterization and quality appraisal of groundwater from Pungar sub basin, Tamilnadu, India. *Journal of King Saud University-Science*, *26*(1), 37-52. https://doi.org/10.1016/j.jksus.2013.08.001

Sun, X., Zhang, H., Zhong, M., Wang, Z., Liang, X., Huang, T., & Huang, H. (2019). Analyses on the temporal and spatial characteristics of water quality in a seagoing river using multivariate statistical techniques: A case study in the Duliujian River, China. *International journal of environmental research and public health*, *16*(6), 1020.https://doi.org/10.3390/ijerph16061020

Tahmasebi, P., Mahmudy-Gharaie, M. H., Ghassemzadeh, F., & Karimi Karouyeh, A. (2018). Assessment of groundwater suitability for irrigation in a gold mine surrounding area, NE Iran. *Environmental earth sciences*, *77*, 1-12. https://doi.org/10.1007/s12665-018-7941-1

Uddin, M., Munna, G., Uddin, A. S. M. R., & Islam, M. (2020). Assessment of Water Quality of Surma River in Perspective of Water Distribution System in Sylhet City. *Int. J. Eng. Sci*, *9*, 8-13. DOI:10.9790/1813-0904010813

Ustaoğlu, F., & Tepe, Y. (2019). Water quality and sediment contamination assessment of Pazarsuyu Stream, Turkey using multivariate statistical methods and pollution indicators. *International Soil and Water Conservation Research*, *7*(1), 47-56. https://doi.org/10.1016/j.iswcr.2018.09.001

Vanham, D., Alfieri, L., Flörke, M., Grimaldi, S., Lorini, V., De Roo, A. and Feyen, L. 2021. The number of people exposed to water stress in relation to how much water is reserved for the environment: A global modelling study. The Lancet Planet Health, Vol. 5, No. 11, Article e766–74. http://doi.org/10.1016/S2542-5196(21)00234-5