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Evaluation of seasonal variation of groundwater quality by using the correlation matrices method in Koppal Taluk, Karnataka, India

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ABSTRACT

Groundwater is a vital, renewable resource that provides over 94% of drinking water in most areas and is critical to human health and sustainable development. Groundwater pollution has a significant impact on human health. This study was conducted in Koppal Taluk, Koppal district, Karnataka, India, from December 2022 to November 2023 to assess the physicochemical parameters of groundwater at 25 seasonal sites. Several steel processing industries are located in the study area, and the inhabitants depend on groundwater sources for their daily needs. The study analyzed the parameters of cations and anions as per APHA guidelines. The study started with data standardization using the water quality index (WQI) and subsequent visualization of correlation matrices and mapping of data plots. The method used was ArcGIS 10.8, which visualizes spatial distribution for data quality control, identification of erroneous data, and classification of different data types. WQI values for drinking water ranged from 9.04 to 75.24 and showed three classes that were unsuitable for drinking. The correlation study showed that TDS, TH, Mg^{2+}, Ca^{2+}, and Cl^{-} were more correlated. Most of the limitations were more or less associated with the parameters. Factor analysis suggested the first three principal components (PCs) in this analysis were 96% (Monsoon), 93.50% (Pre-Monsoon), and 87% (Post-Monsoon) of the cumulative variance correspondingly, and TDS was the most representative variable across all seasons. This study underlined the importance of sustainable development and groundwater protection. The recommendations could help groundwater managers and urban planners to improve and maintain groundwater quality.

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1. Introduction

Groundwater, situated beneath the terrestrial crust within aquifers, plays a key role in supporting ecosystems, agricultural methodologies, and satisfying the water stresses of human societies. Its unique features classify it as pivotal for an array of purposes and as a key player in the Earth's water management system [1]. The chemical characteristics of groundwater elucidate hydrobiological interactions and furnish valuable insights into ecosystem metabolism [2]. Local Earth's crust, atmospheric conditions, and human activity all influence the physicochemical properties of groundwater [3]. The application of pesticides and fertilizers, although enhancing agricultural yields, negatively influences water quality [4]. Fluctuations in groundwater quality are affected by hydrological factors, anthropogenic influences, and components of recharged water [5]. Due to inadequate freshwater supplies, the quality of drinking water presents a significant challenge in numerous regions, rendering the assessment of water quality imperative for the long-term management of these vital natural resources. Groundwater holds specific significance to human activities due to its stable temperature, inherent quality, extensive availability, and comparatively reduced susceptibility in contrast to surface freshwater sources [6]. Effective management of integrated water resources requires a thorough assessment of all available drinking water resources, including groundwater, surface water, and drainage systems for households and farms [7].

In India, the phenomena of accelerated economic growth, demographic expansion, and urbanization have strongly influenced the quality and accessibility of groundwater. Merging various water quality indicators into an understandable metric is of the utmost importance [8]. Both urban and rural populations rely on groundwater for both domestic consumption and agricultural needs, with agriculture accounting for approximately 43% of global groundwater use [9-11]. Groundwater contamination leads to scarcity of water supplies and increased costs for remediation and securing alternative water sources [12]. India needs to improve public health standards and access to drinking water, as ongoing water quality assessments are critical to understanding human impacts on water resources [13]. Water quality management is complicated by a combination of natural and man-made factors, compounded by a lack of systematic data in developing countries [14]. Numerous studies have focused on assessing and monitoring groundwater pollution and quality, as both are directly linked to human health [15-19]. In this study, the research area was selected because of the presence of steel processing industries, as well as other variables, such as traditional agricultural practices, irrigation methods, erratic rainfall patterns, indiscriminate groundwater extraction, and challenges such as salinity, brackishness and contamination by nitrate and fluoride, along the major river systems in Koppal Taluk [20]. The habitats in these regions are dependent on the groundwater for their daily needs. Therefore, a systematic analysis of groundwater quality in Koppal Taluk was conducted. Unlike previous studies that focused on a limited number of parameters, this study evaluated the suitability of groundwater based on a comprehensive range of hydrochemical characteristics. The water quality index, spatial distribution analysis using ArcGIS 10.8, regression analysis, and Pearson's correlation analysis were used to investigate the potability of the water [21]. A comparative analysis with the criteria established by the APHA [22], WHO [23], and BIS [24] establishes both national and international standards. This methodological approach improved data interpretation and provided important insights into the factors influencing the purity of groundwater in Koppal Taluk, providing quality groundwater for domestic and agricultural needs and societal benefit.

2. Material and Methods

2.1 Geology of study area

Koppal Taluk is situated in the Koppal district in Karnataka, India, and is characterized by its diverse geological features. The region consists mainly of black and red soils typical of the Deccan Plateau. The soils are known for their low to medium water-holding capacity and moderate fertility. On the other hand, the red soils are mostly sandy to loamy and slightly to moderately alkaline. The soils are less fertile as compared to the black soils but can be improved through proper management practices. Koppal Taluk is known for its mineral resources, including granite, limestone, and iron ore. The occurrence of these minerals contributes to the local economy and provides opportunities for mining and related industries [20].

2.2 Description of the study area

On August 25, 1997, the Raichur District in Karnataka was divided into the Koppal district, which covers a geographical area of about 1375 square kilometers. Koppal is located in the erstwhile Hyderabad-Karnataka region and is considered the most backward district of the state. The study region lies between latitudes 15°6'0" N and 15°36'0" N and longitudes 75°54'0" E and 76°24'0" E. According to the 2011 census, a total of 1,391,292 people live in the study area in 588 inhabited and 40 empty settlements. With an average annual rainfall of 572 mm, the Koppal region experiences scorching summers and minimal rainfall due to its semi-arid environment. The overall literacy rate of the district is 55%, with 69% of males and 40% of females being literate. The study was conducted in Koppal Taluk, a part of the Krishna Basin [20].

2.3 Groundwater sampling and analysis

Twenty-five different sampling points were selected for monitoring the physico-chemical parameters of the groundwater from December 2022 to November 2023, taking into account seasonal fluctuations. Study area map is shown in Fig.1. The bottles were soaked in a 10% nitric acid solution before sampling to prevent chemical interactions with the sample elements. All samples were collected according to APHA 2000 guidelines [22] and were brought to the laboratory immediately after collection in sterile, acid-treated polyethylene terephthalate (PET) containers and stored in a freezer at 4°C. This procedure reduced the possibility of microbial growth and flocculation as well as adsorption to the envelope surfaces, all of which could affect the results. The collected groundwater samples were appraised within 30 days of their collection date. Blank samples and relevant certified standard materials were analyzed as unknowns for each sample batch. The margins of error for the selected ion appraised will be less than ±5%. The groundwater samples are analyzed according to APHA criteria. After analysis, the correctness of each sample was determined by calculating the percentage error [25].

2.4 Methodology

2.4.1 Water Quality Index (WQI)

The WHO drinking water standards (1984) [23] were used to calculate the WQI. The weighting of selected water quality variables was inversely compared to the proposed standards for the respective variables [26-28].

The calculation was comprised of three different stages. In the first stage, nine parameters (Ca^{2+}, Mg^{2+}, SO_4^{2-}, Cl^-, NO_3^-, pH, TDS, EC, F^-) were weighted depending on their health effect (Table 1).

Parameters such as TDS, SO_4^{2-}, and Cl^- were given the highest (five) weighting due to their importance for the appraisal of water quality [29]. Ca^{2+} and Mg^{2+} were given a weight range from 1 to 5 for the overall analytical quality of the drinking water [27]. In the second stage, the relative weight (Wi) of each variable was compared using Equation 1.

$$W_i = \frac{w_i}{\sum_{i=1}^{n} w_i} \quad (1)$$

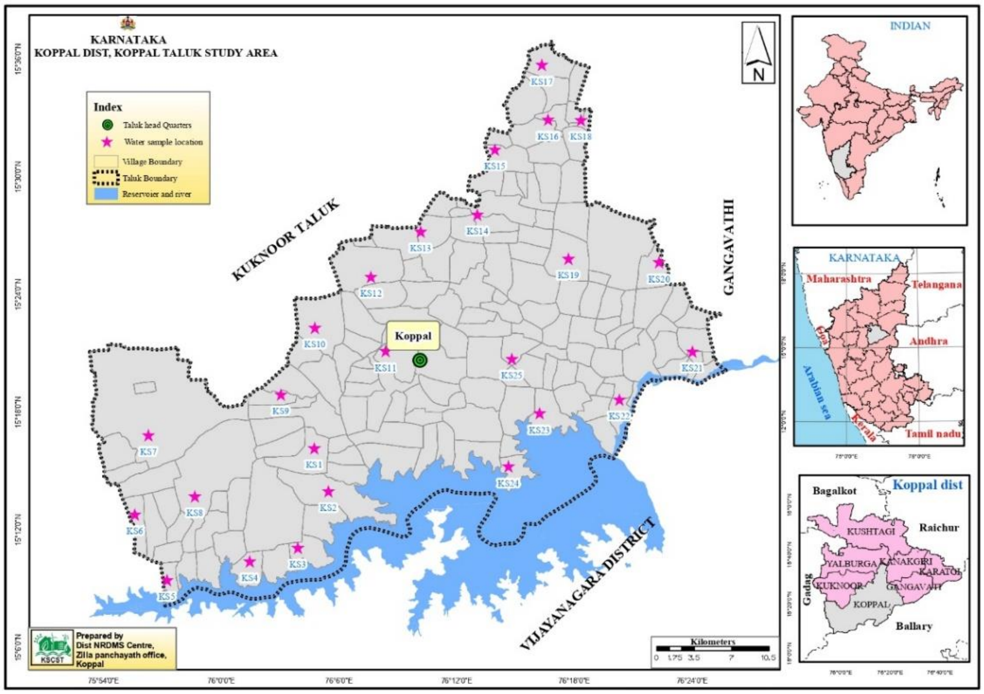

Fig. 1. Study area covering the Koppal Taluk Koppal District.

Table 1. Standards of Water Quality Value (in *PPM*).

Parameter	WHO Standard	Weight (w_i)	Relative weight (W_i)
pH	8.5	3	0.103
TDS	500	5	0.179
Chloride	250	5	0.179
Sulphate	250	5	0.179
EC	200	4	0.143
Nitrate	12	2	0.071
Fluoride	120	1	0.036
Calcium	75	3	0.107
Magnesium	50	3	0.107
		$\Sigma\ w_i = 28$	$\Sigma\ W_i = 1$

The assigned weight (w_i), taken as a relative weight (W_i), and the prescribed WHO standards for individual parameters are listed in Table 1. In the third step, the analytical quality rating scale (q_i) was considered for individual parameters adopting Eq. 2:

$$q_i = \frac{C_i}{S_i} X100 \quad (2)$$

where q_i is the quality ranking, C_i is the concentration of individual parameters in each groundwater sample (ppm), and S_i is the WHO standard for individual parameters (ppm) (Table 1). In the final step, the water quality sub-index (SI_i) is first calculated for each parameter and then used to compute the WQI for each groundwater sample using equation 3 and equation 4 given below

$$SI_i = W_i \times q_i \quad (3)$$

$$WQI = \sum SI_i \quad (4)$$

where SI_i is the sub-index of the ith parameter, q_i is the rating of concentration of the ith parameter, and n is the number. The procedure of WQI estimation is deliberated in detail [8,30-33]. Computed WQI values are usually classified groundwater samples into five categories : excellent, good, poor, very poor and unsuitable for drinking water [34].

2.4.2 Spatial distribution

Geographic information systems (GIS) have become an important tool for apprising and exhibiting spatial data and facilitating decisions in various fields [35]. Spatial Analyst, an extension of ArcGIS 10.8, was used to analyze the spatio-temporal characteristics of the groundwater quality parameters (ESRI, 1999) [36]. This technique is a precise discontinuity to estimate the best linear equilibrium and ensure minimum variance of the estimation error [37]. Groundwater quality classification maps for different parameters, expressed by thematic maps based on the standard WHO guidelines values for drinking water, are pointed out by applying GIS techniques to estimate their spatial distribution in the study area. The correlation coefficient (r) is calculated using Equation 5.

$$r = \frac{n\Sigma xy\Sigma - x\Sigma y}{\sqrt{[n\Sigma x^2 - -(\Sigma x)^2][n\Sigma y^2 - -(\Sigma y)^2]}} \quad (5)$$

where x and y are two properties, (X_i, Y_i) be n sets of recognized values of (I = 1 to n) parameters and in the equation r among the parameters x and y.
The regression analysis was carried out using the statistical software SPSS 11.0, the calculation of correlations between different water quality measures is essential for predicting or forecasting water quality [38]. With values approaching +1 or -1, the correlation coefficient matrix indicates the possibility of a linear relationship with two variables, x and y [39].

2.4.3 Pearson's correlation matrix

The Pearson correlation matrix was used to analyze the relationships between the variables and to illustrate their correlations. The correlation matrix of the groundwater quality parameters, expressed by the correlation coefficient (r) and the significance level ($\rho = 0.05$), which showed that the variables with ($r > 0.75$) were highly correlated at a significance level ($\rho < 0.05$); the variables with ($0.5 < r < 0.75$) showed a reasonable or moderate relationship at the same significance level. The analysis showed that some parameters had a strong association, suggesting a common source or similar trend due to factors such as water-rock interaction and ion exchange. In addition, variables with correlation coefficients $0.01 < r < 0.5$, were weak, and a perfect negative association was observed when coefficients were $r < 0$ at a significance of $\rho < 0.05$ [38].

2.4.4 Factor analysis

An important statistical technique for analyzing geochemical data is factor analysis, which pinpoints the critical variables affecting the aquifer system. Reducing a large number of variables to a smaller number of components is the main component [40,41]. FA's primary goals are to consolidate the data organization obtained by PCA progressively and reduce the influence of less significant factors. The analysis focused only on factors with eigenvalues greater than one, which provide relevant information on the datasets. This approach helped to uncover the sources and factors responsible for controlling GW quality. The three principal component analyses (PCA) combined explain a variation of data, representing all of the components adequately. Additional variables called Vari-factors are created by rotating the PCA-defined axis to do this [42]. By creating new orthogonal and independently associated latent variables from an ordered combination of the data as originally collected, PCA reduces the dimensionality of the data [43].
Principal Component Analysis is frequently used to convert high-dimensional data into a lower-dimensional representation for exploratory reasons. It is possible to efficiently reduce a large number of linked variables in the original dataset to a smaller collection of unconnected variables, known as PC or axis [44]. The lists of coefficients known as eigenvectors, which are linearly independent (orthogonal) variables (sometimes referred to as weightings), and the initial correlated variables comprise these variables. The first PC defines the highest percentage of the dataset's variation, while successive PCs explain the remaining fraction. With a decreasing contribution to the overall variance, the PCs are composed of an increasing number of components [45]. The Kaiser-Meyer-Olkin (KMO) and Bartlett's tests were used to determine if the data was suitable for factor analysis. Specifically, the adequacy of the sample for each variable in the model was evaluated. While a KMO score below 0.5 indicated that the data would not be appropriate for factor analysis, a value between 0.5 and 0.8 was

acceptable [46]. In this study, the Kaiser-Meyer-Olkin (KMO) coefficient was 0.62, Bartlett's Test of Sphericity values were less than 0.05, and the number of factors depended on eigenvalues greater than one.

Using Origin 2024b software, R-mode factor analysis was used to group the parameters according to similarity [47]. The results obtained for analysis of correlation (CA) and FA were standardized to prevent misclassification resulting from different measurement units. By comprehending their underlying associations, this method seeks to minimize the number of original variables. The study's claimed significance levels were all at $\rho < 0.05$.

3. Results and Discussion

3.1 Seasonal fluctuation of physical parameters

The seasonal fluctuations of physicochemical parameters in groundwater quality are shown in Figure 2 and statistical parameters during Monsoon, Pre-monsoon and post-monsoon seasons are shown in Table 2. The pH is a key factor influencing the nutrient level, heavy metals, and other constituents in water [34]. In this study, the pH ranged between 6.25 and 7.99, with the following seasonal variations: Monsoon (6.17–7.99), Pre-Monsoon (6.12–7.98), and Post-Monsoon (6.42–7.62). These values indicate water quality varying from slightly acidic to slightly alkaline and within the permissible limit (6.50–8.50) [28]. Interestingly, the pH was generally the highest during the Monsoon, in support of the findings of Giao et al. [48], who reported average groundwater pH values of 7.36 ± 0.13 (dry season) and 7.32 ± 0.33 (wet season) in Can Tho City. Seasonal variations in the pH remained within the acceptable range (6.50–8.50). Higher pH values during the season were attributed to the dilution of rainwater, in contrast to studies from Can Tho City, where pH values were higher in the dry season due to evaporation and lower dilution. The Post-Monsoon increase in pH reflects the effects of natural buffering through water-rock interaction and dilution of acidic inputs, while Pre-Monsoon conditions reflect isolated aquifers with limited recharge [48,49].

Total dissolved solids (TDS), an indicator of groundwater salinity [50], ranged from 382.00 to 3652.00 ppm. According to WHO guidelines (2017), TDS > 500.00 ppm is undesirable for drinking water [28]. The study measured electrical conductivity (EC) using a Conductivity Bridge and TDS via the evaporation method, adhering to APHA guidelines [22]. Maximum EC was observed at Bisarahalli (KS-1) across all seasons, while the lowest EC was at Kawaloor (KS-7) during the Post-Monsoon. The lowest TDS (382.00 ppm) was recorded at Hirekasanakandi (KS-23) during the Pre-Monsoon, while the highest (3652.00 ppm) was at Alawandi (KS-8) in the Post-Monsoon. High TDS values indicated significant mineralization, which can affect water taste [51,28]. Figures 2.1 and 2.2 depict spatial distributions of TDS and EC. These findings align with Tran et al. [52], who reported seawater intrusion with TDS ranging from 82.00 to 12,950.00 ppm in certain areas, while in neighbouring Bac Lieu Province, Giao et al. [53] showed lower TDS values (286.00–715.00 ppm). The total dissolved solids were significantly lower during the Monsoon due to dilution from rainwater, while Post-Monsoon levels increased, reflecting enhanced mineralization from recharge events. The highest TDS values indicated salinity concerns in certain areas, consistent with seawater intrusion patterns reported in similar studies [53]. Seasonal changes in TDS highlighted the significant influence of recharge and mineral leaching. The Post-Monsoon peak was accentuated by the cumulative effect of rainfall infiltration and reduced dilution due to residual water reserves.

The total hardness (TH), measured by the titrimetric method of the disodium salt of EDTA, was affected by Ca^{2+} and Mg^{2+} ions as well as carbonates, bicarbonates, chlorides, and sulfates [54]. The lowest TH values were measured in Madinoor (KS12) during the Pre-Monsoon (63.60 ppm) and in Hirekasanakandi (KS-23) during the Monsoon (107.00 ppm) and Post-Monsoon (164.00 ppm). The maximum TH value was 1254.00 ppm in Tigari (KS-4) during the Post-Monsoon. The maps of the spatial distribution of TH are shown in Figure 2.3. These results are in agreement with studies from the Shagamu industrial area [55] and Kavaratti Island, Lakshadweep (India) [56]. During and immediately after the monsoon season, rain seeps into the soil, replenishing aquifers and dissolving minerals from soil and rocks. This leads to an enhancement in the concentration of dissolved ions and minerals in the groundwater, resulting in higher values of TDS, total hardness, calcium, magnesium, chloride, and sulfate [56]. The peak hardness values after the Monsoon are due to the enhanced dissolution of minerals and subsequent concentration due to evaporation. Pre-Monsoon conditions, on the other hand, reflect the stagnation of relatively soft water.

Sulfate (SO_4^{2-}) concentrations measured using the barium chloride method with UV-VIS-169 Systronics (420 nm) ranged from 19.39 to 340.00 ppm, remaining within the standard limit of 400.00 ppm. Seasonal variations were as follows: Monsoon (30.83–289.40 ppm), Pre-Monsoon (19.39–232.57 ppm), and Post-Monsoon (minimum values at Sidaganahalli (KS-15), Budshetnal (KS-13) and Hirekasanakandi (KS-23), respectively. Figure 2.4 shows the SO_4^{2-} distribution, suggesting that seawater intrusion contributed during the dry seasons due to lower rainfall and upstream flow. Seasonal variations in sulfate concentrations indicated higher contributions from natural leaching during the monsoon accumulation and lower contributions during the dry Pre-Monsoon season. Overall, the concentrations remained within the standard limits [28]. Sulfate concentrations are often associated with agricultural runoff. Monsoon rains activate the sulfate compounds, which seep into the groundwater and cause peak values after the monsoon. Pre-Monsoon levels are lower as there is less surface water runoff, and leaching activity is minimal [56]. Seasonal differences in sulfate levels illustrated the role of rainfall in the mobilization of sulfates. Peak values after the monsoon indicated enhanced leaching and replenishment of the groundwater [54].

The chloride (Cl^-) concentrations measured with the argentometric titration method ranged from 19.14 to 1253.00 ppm and frequently exceeded the permissible limit of 250.00 ppm. The highest Cl^- concentration (1253.00 ppm) was measured at Kawaloor (KS-7) during the Post-Monsoon, while the lowest (19.14 ppm) was measured at Sidaganahalli (KS-15) during the Pre-Monsoon, probably due to dilution caused by rain. The average Cl^- concentrations were 308.00 ppm (Pre-Monsoon/Monsoon) and 331.86 ppm (Post-Monsoon). Figure 2.5 depicts spatial Cl^- distribution. Excessive abstraction during dry seasons could lead to the infiltration of contaminated water, increasing Cl^- concentrations, while rain dilutes the concentrations. High Cl^- and SO_4^{2-} levels could affect the quality of irrigation water and corrode water distribution systems [28]. After the monsoon, chloride levels peaked due to over-extraction and less dilution, while the lower concentrations during the Pre-Monsoon reflected the limited water-rock interactions and dilution by rain. The seasonal variations in chloride reflected the interaction of accumulation, dilution, and human activities. The peaks after the monsoon were consistent with the mobilization of salts and a lower volume of water [57].

The analysis of fluoride (F^-), performed using the SPADNS method according to APHA guidelines [22], revealed mean concentrations of 0.74 ppm (Pre-Monsoon), 0.86 ppm (Monsoon), and 1.03 ppm (Post-Monsoon). Peak values included 1.33 ppm in Bisarahalli (KS-1, Monsoon), 1.25 ppm in Handral (KS-9, Pre-Monsoon), and 2.02 ppm in Keslapur (KS-5, Post-Monsoon). Spatial fluoride maps can be found in Figure 2.6. The granitic rocks of the region, which are rich in fluoride-containing minerals such as feldspar, probably contributed to the elevated F^- values [27]. Seasonal increase in fluoride concentrations after the monsoon highlighted the interaction of groundwater with fluoride-rich granitic rocks during recharge. Areas with higher fluoride concentrations could pose a potential health risk [29]. Seasonal fluoride variations were related to the extent of water-rock interaction. Post-Monsoon conditions increased the mobilization of fluoride ions, while Pre-Monsoon levels remained stable.

The composition of the main ions of the groundwater followed the order $Ca^{2+} > Mg^{2+}$ and $SO_4^{2-} > Cl^- > NO_3^-$. Calcium levels affected by carbonates, sulfates, and chlorides ranged from 8.00 ppm (Madinoor, KS-12, Pre-Monsoon) to 816 ppm (Bisarahalli, KS-1, Post-Monsoon), with 56% exceeding the acceptable limit of 75.00 ppm. Most samples remained below the WHO limit of 200.00 ppm [28]. Figure 2.7 illustrates the calcium distributions. Similarly, measured magnesium values ranged from 8.55 ppm (Koppal, KS-11, Monsoon) to 230.00 ppm (Bisarahalli, KS-1 Pre-Monsoon) and averaged 65.00 ppm. Spatial maps for Mg^{2+} can be found in Figure 2.8. Both ions showed higher concentrations after the monsoon, which might be due to the enhanced closure of minerals from the rock formations during recharge [58]. Their spatial distribution was consistent with local geologic features. The seasonal contrast emphasized the dependence of the calcium content on active recharge and dissolution processes. After the monsoon, these effects were amplified due to the prolonged contact between the water and rock. Seasonal magnesium variations were consistent with mineral dissolution due to enrichment, with the Post-Monsoon increase reflecting increased leaching and evaporation. Nitrate (NO_3^-), which is essential for plant growth but is contaminated by fertilizers and waste, ranged from 3.06 ppm (Ginigera, KS-25) to 39.86 ppm (Bisarahalli, KS-1) during the Pre-Monsoon, with an average of 14.82 ppm. High NO_3^- levels pose a health risk, especially for children. Spatial maps for NO_3^- are shown in Figure 2.9 [15,59]. Nitrate levels were higher before the monsoon due to agricultural runoff and fertilizer application, while the monsoon rains diluted nitrate concentrations, and levels decreased after the monsoon. Nitrate concentrations are often associated with agricultural runoff and natural leaching. The monsoon rains mobilize these compounds into the groundwater, leading to Post-Monsoon peaks. Pre-Monsoon levels were lower due to lower surface water flow and minimal leaching activity. Anthropogenic activities and seasonal dilution influenced the nitrate levels. The peak values before the monsoon are due to concentrated inputs from agriculture, while the values after the monsoon reflect dilution by rainwater [60].

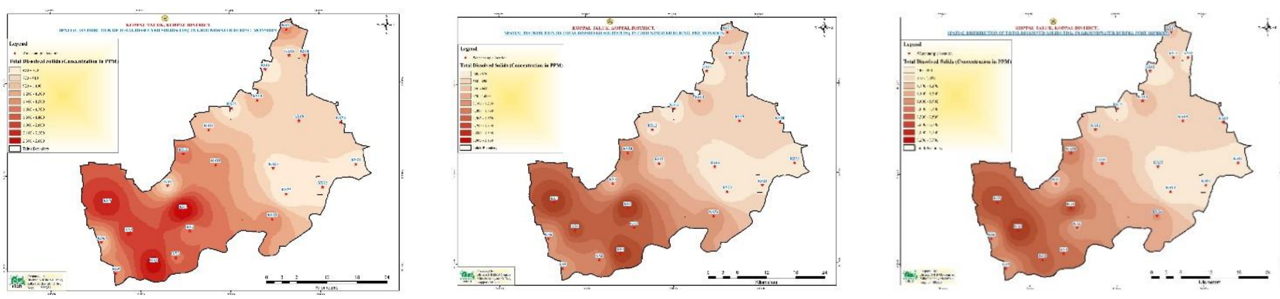

Fig. 2.1 Spatial distribution of TDS during Monsoon, Pre-monsoon and Post-monsoon seasons.

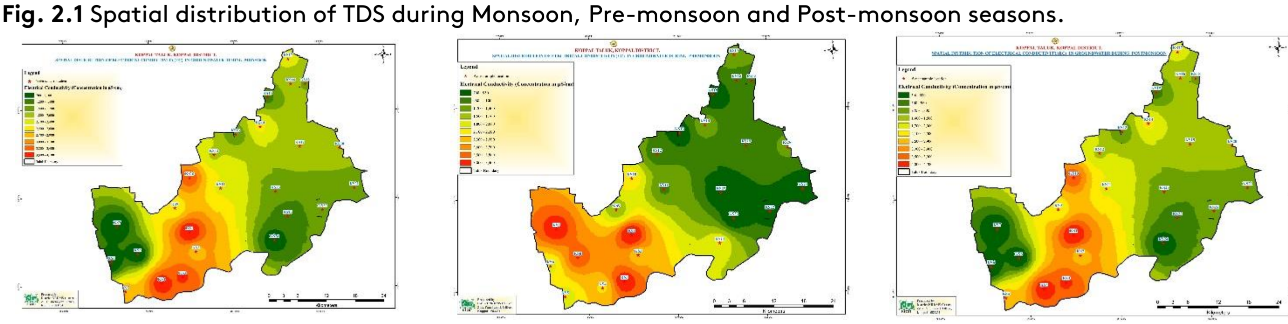

Fig. 2.2. Spatial distribution of EC during Monsoon, Pre-monsoon, and Post-monsoon seasons.

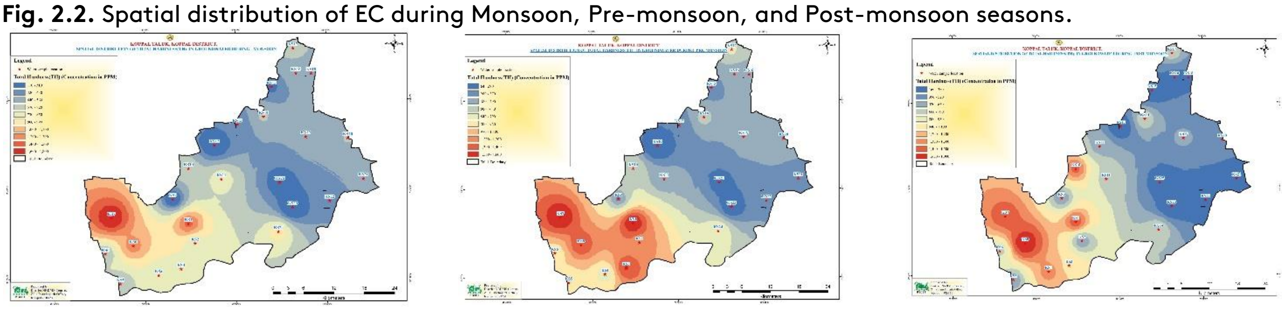

Fig. 2.3. Spatial distribution of TH during Monsoon, Pre-monsoon, and Post-monsoon seasons.

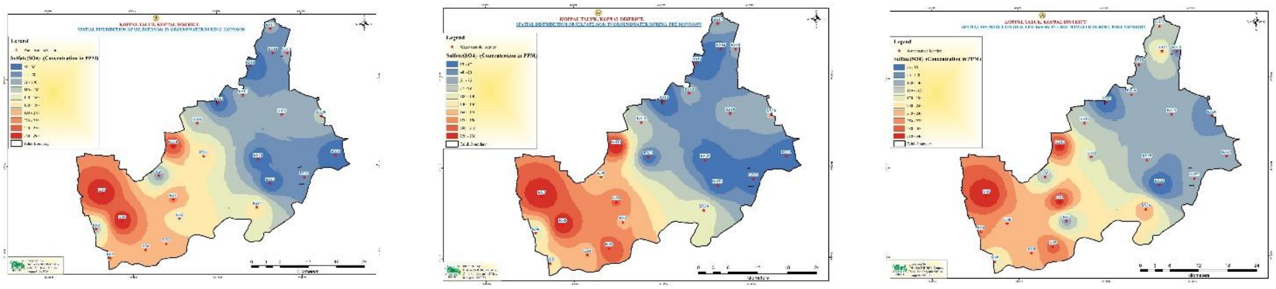

Fig. 2.4. Spatial distribution of Sulfate during Monsoon, Pre-monsoon and Post-monsoon seasons.

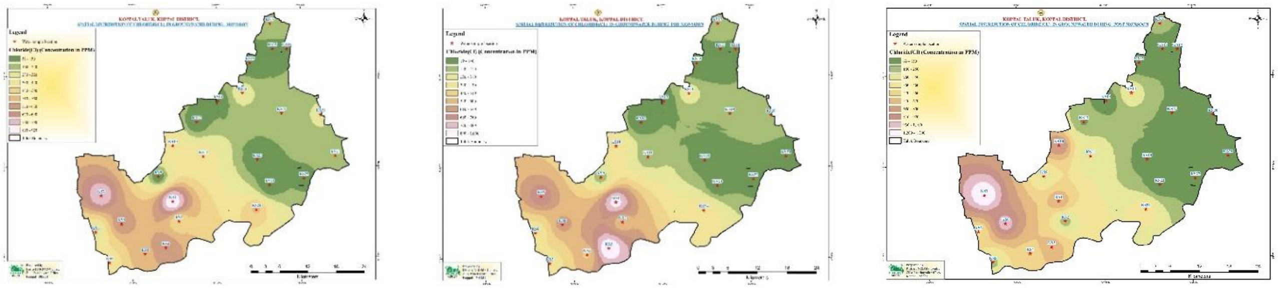

Fig. 2.5. Spatial distribution of chloride during Monsoon, Pre-monsoon and Post-monsoon seasons.

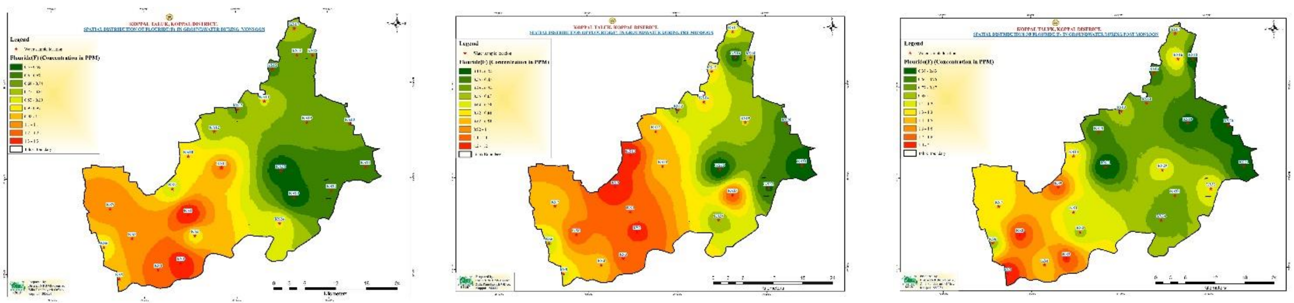

Fig. 2.6. Spatial distribution of fluoride during Monsoon, Pre-monsoon and Post-monsoon seasons.

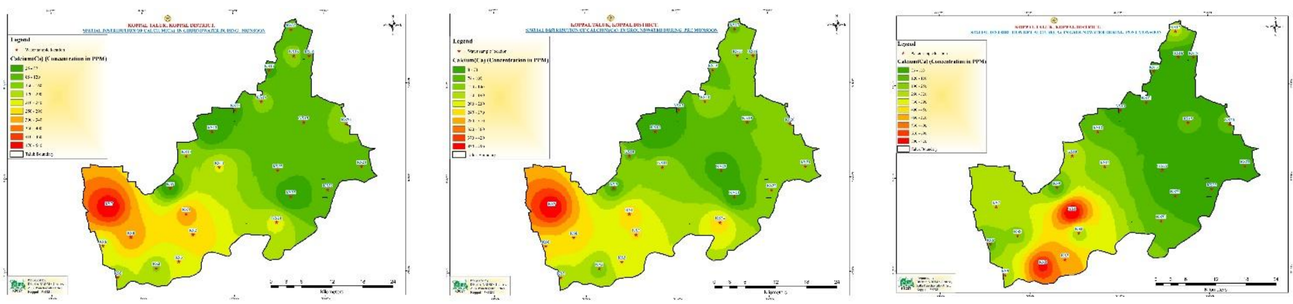

Fig. 2.7. Spatial distribution of calcium during Monsoon, Pre-monsoon and Post-monsoon seasons.

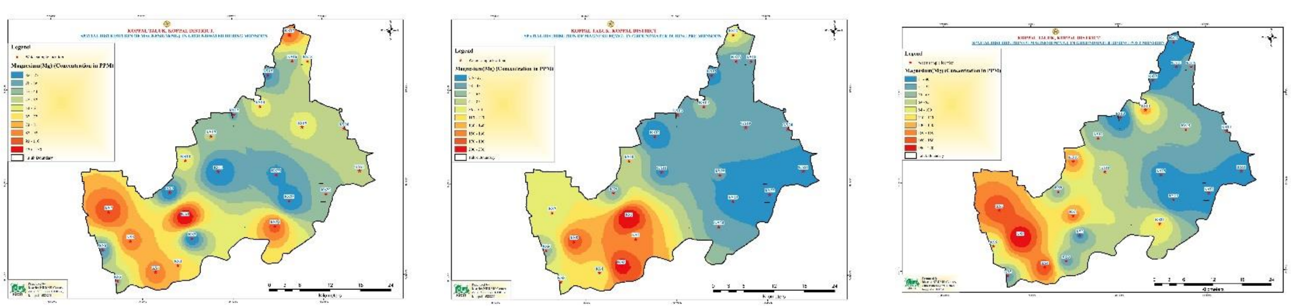

Fig. 2.8. Spatial distribution of magnesium during Monsoon, Pre-monsoon and Post-monsoon seasons.

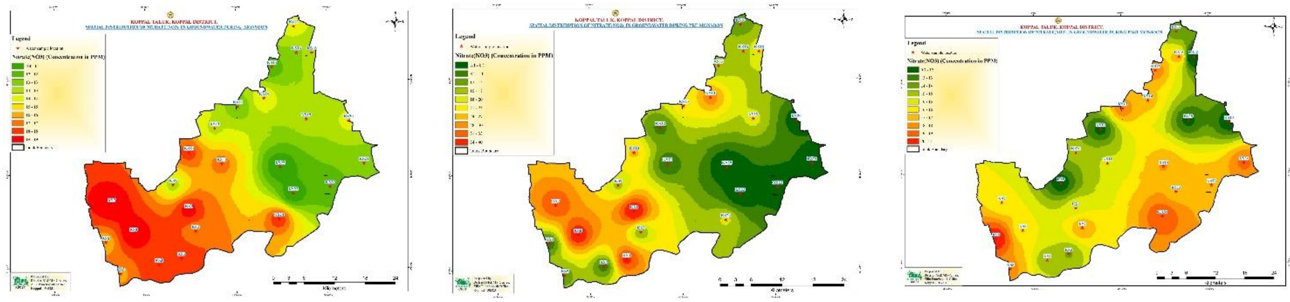

Fig. 2.9. Spatial distribution of nitrate during Monsoon, Pre-monsoon and Post-monsoon seasons.

Fig 2. Spatial distribution of physicochemical parameters during Monsoon, Pre-Monsoon, and Post-Monsoon seasons.

Table 2. Descriptive Statistics of the Monsoon, Pre-Monsoon, and Post-Monsoon seasons (in *ppm, EC in µS/cm)*.

Variable	Monsoon				Pre-Monsoon				Post-Monsoon			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
EC	1939.00	982.69	700.00	4100.00	1612.00	855.04	700.00	3400.00	1739.00	1323.00	4.95	4680.00
TDS	1224.00	606.78	448.00	2624.00	971.00	550.52	382.00	2114.00	1440.00	878.60	432.00	3652.00
TH	621.12	386.92	107.00	1757.00	647.00	446.17	63.60	1590.00	698.19	462.32	164.00	1852.00
Ca	163.63	114.36	24.48	538.56	146.00	102.20	8.00	492.00	206.98	203.48	32.56	816.00
Mg	53.26	32.80	8.55	132.19	68.00	62.33	9.52	230.85	73.75	57.58	11.05	220.40
Cl	308.89	243.42	52.25	918.86	308.00	282.36	19.14	1048.00	331.86	321.22	62.52	1253.00
F	0.86	0.23	0.50	1.33	0.74	0.31	0.19	1.25	1.03	0.45	0.37	2.02
SO_4	130.60	78.05	30.83	289.40	105.05	71.65	19.39	232.57	174.56	80.95	46.00	340.00
NO_3	14.53	3.04	9.44	17.13	14.53	10.69	3.06	39.86	15.42	2.80	9.69	21.20

Source: Author's Calculation, SD: Standard Deviation

3.2 Water quality index analysis

The WQI at specific sampling points is shown in Table 3. The calculated WQI values varied from 9.04 to 75.24. According to the WQI classification, this appraisal was based on Embaby et al. [61], who used WQI in the appraisal of groundwater quality. The present study revealed that about 60% of the groundwater samples analyzed were classified as "poor" and 28% were classified as "good". The remaining (16%) that were in the middle of the selected area were classified as "excellent," which was often consistent with the study and could be used as drinking water (Table 3). The high value of WQI was related to the greater amount of TDS, EC, and TH. These results outlined that the groundwater was only suitable for consumption.

3.3 Pearson's correlation results

The initial step in factor estimation involves the application of correlation techniques to identify the degree and strength of the association between the linearly different variables. This is done using the "Pearson correlation matrix" using SPSS. The analysis is primarily based on data from 25 boreholes, focusing on the physico-chemical constituents of the major elements.

Tables 4 and 5 show the correlation coefficients of selected data of some parameters from the Monsoon and Pre-Monsoon seasons correspondingly. Significant positive relationships between Ca^{2+}, Mg^{2+}, Cl^-, SO_4^{2-}, and NO_3^- were identified during both the Pre-Monsoon and Monsoon periods, indicating that these compounds contribute significantly to TDS and TH in the groundwater of this research location. A significant association between Ca^{2+}, Mg^{2+}, and Cl^-, SO_4^{2-} and NO_3^- ions indicated that groundwater samples were heavily contaminated by these components as a result of over-exploitation and human activities. The major source of Ca^{2+} and Mg^{2+} ions in groundwater might be the mineral exchange between the rocks and water. Dhilleshwar Rao et al. found similar findings throughout the Monsoon and Post-Monsoon seasons [62]. Stricter regulations on salinity and ion concentration in groundwater are necessary to preserve water quality and ecosystem health, as evidenced by the strong correlations between the parameters during the Pre-Monsoon and Post-Monsoon periods [63].

During the Post-Monsoon season, TH, Mg^{2+}, and SO_4^{2-} significantly correlated with TDS and Cl^-, as shown in Table 6. This may suggest that the dilution effects from the Monsoon rains were subsiding, allowing for the concentration of these ions due to evaporation or reduced recharge rates. In the Pre-Monsoon season, the presence of TH and EC alongside TDS and Cl^- indicated that groundwater quality might be affected by increased evaporation rate. In the Monsoon season, the influence of EC, SO_4^{2-}, F^-, and NO_3^- alongside TDS and Cl^- suggested that the influx of rainwater could lead to the leaching of contaminants into the groundwater system, particularly from surface sources. This season often sees increased runoff, which can carry fertilizers and other pollutants into aquifers. The consistent strong positive loading of TDS and Cl^- across all seasons indicated that these parameters were likely influenced by similar sources or processes, such as agricultural runoff or urban discharge, which can elevate their concentrations in groundwater [64,65].

Multiple regression tools were used to standardize coefficients to appraise which self-regulating quality parameters had the most significant effect depending on WQI. The B coefficient indicates the predictive power of each parameter in the model. The primary highlight is on appraising the encouragement of these parameters; regression values are given in Table 7, indicating that most of the parameters were statistically significant ($p < 0.001$) to the WQI. However, Mg^{2+}, Ca^{2+}, and Cl^- had the most substantial impact, indicated by the maximum standardized beta-coefficients (Table 7), which highlights Mg^{2+}, Ca^{2+}, and Cl^- as critical indicators of groundwater quality.

Table 3. Places of location of groundwater samples collected during the Monsoon, Pre-Monsoon and Post-Monsoon seasons in and around Koppal Taluk.

Sl No	Sampling Station Code	Sampling Station	WQI	WQ Status	Class
1	KS-01	Bisarahalli	46.63	Good	II
2	KS-02	Katarakigudlanor	67.15	Poor	III
3	KS-03	Mattur	42.95	Good	II
4	KS-04	Tigari	58.28	Poor	III
5	KS-05	Keslapur	64.56	Poor	III
6	KS-06	Belagatti	70.60	Poor	III
7	KS-07	Kawaloor	48.02	Good	II
8	KS-08	Alawandi	43.94	Good	II
9	KS-09	Handral	75.24	Poor	III
10	KS-10	Halageri	61.32	Poor	III
11	KS-11	Koppal	71.33	Poor	III
12	KS-12	Madinoor	49.72	Good	II
13	KS-13	Budshetnal	25.49	Excellent	I
14	KS-14	Irkalagada	75.11	Poor	III
15	KS-15	Sidaganahalli	9.04	Excellent	I
16	KS-16	Chikkasulikeri	58.82	Poor	III
17	KS-17	Hirebommanal	72.11	Poor	III
18	KS-18	Ganganal	55.67	Poor	III
19	KS-19	Kukanapalli	66.86	Poor	III
20	KS-20	Jabbalagudda	66.50	Poor	III
21	KS-21	Basapur	32.80	Good	II
22	KS-22	Huligi	37.25	Good	II
23	KS-23	Hirekasanakandi	20.77	Excellent	I
24	KS-24	Karkihalli	68.02	Poor	III
25	KS-25	Ginigera	15.86	Excellent	I

Table 4. The correlation matrix of groundwater in the Monsoon season for Koppal Taluk.

	EC	TDS	TH	Ca	Mg	Cl	F	SO_4	NO_3
EC	1*								
TDS	0.99*	1*							
TH	0.86*	0.85*	1*						
Ca	0.77*	0.76*	0.96*	1*					
Mg	0.77*	0.75*	0.73*	0.56*	1*				
Cl	0.95*	0.94*	0.92*	0.85*	0.75*	1			
F	0.90*	0.89*	0.75*	0.68*	0.57*	0.89*	1		
SO_4	0.88*	0.87*	0.80*	0.78*	0.58*	0.86*	0.83*	1	
NO_3	0.93*	0.9*	0.85*	0.79*	0.64*	0.92*	0.91*	0.94*	1

A two-tailed test of significance is used; * Correlation is significant at a 0.05 level.

Table 5. The correlation matrix of groundwater in the Pre-Monsoon season for Koppal Taluk.

	EC	TDS	TH	Ca	Mg	Cl	F	SO_4	NO_3
EC	1*								
TDS	0.99*	1*							
TH	0.95*	0.97*	1*						
Ca	0.79*	0.80*	0.87*	1*					
Mg	0.88*	0.89*	0.87*	0.52*	1*				
Cl	0.97*	0.97*	0.94*	0.73*	0.90*	1*			
F	0.55*	0.56*	0.42*	0.18*	0.55*	0.49*	1*		
SO_4	0.92*	0.91*	0.82*	0.66*	0.77*	0.83*	0.66*	1*	
NO_3	0.75*	0.75*	0.75*	0.58*	0.72*	0.74*	0.49*	0.66*	1

A two-tailed test of significance is used; * Correlation is significant at a 0.05 level.

Table 6. The correlation matrix of groundwater in the Post-Monsoon season for Koppal Taluk.

	EC	TDS	TH	Ca	Mg	Cl	F	SO_4	NO_3
EC	1*								
TDS	0.31*	1*							
TH	0.31*	0.96*	1*						
Ca	0.77*	0.72*	0.69*	1*					
Mg	0.14*	0.86*	0.90*	0.52*	1*				
Cl	0.12*	0.92*	0.92*	0.54*	0.85*	1*			
F	0.28*	0.55*	0.41*	0.36*	0.28*	0.44*	1*		
SO_4	0.31*	0.83*	0.82*	0.66*	0.71*	0.85*	0.44*	1*	
NO_3	-0.32*	-0.02*	-0.14*	-0.15*	-0.05*	-0.01*	0.08*	0.09*	1

A two-tailed test of significance is used; * Correlation is significant at a 0.05 level.

Table 7. Multiple regression appraisal to estimate the variables contributing to the WQI.

Physico-chemical variables	B coefficient	Standard error	Standardized beta	Rank	P value
TDS	0.0348	0.0000004	0.030	VII	0.001*
Cl	0.0715	0.0000007	0.832	I	0.001*
SO_4	0.0714	0.0000006	0.032	VI	0.001*
Ca	0.1426	0.0000003	0.422	II	0.001*
Mg	0.2130	0.0000005	0.266	III	0.001*

* Highly Significantly Correlated.

3.4 Factor analysis

The first three principal components (PCs) in this analysis were found to be 96%, 93.5%, and 87% of the cumulative variance for the Monsoon, Pre-Monsoon, and Post-Monsoon seasons, respectively. PC1 accounted for 78.708%, PC2 for 10.255%, and PC3 for 4.545% of the disparity in the Pre-Monsoon sample. PC1 explained 84.569%, PC2 6.105%, and PC3 5.345% of the degree of variability in the monsoon season dataset. During the Post-Monsoon season, PC1 explained 59.511%, PC2 accounted for 16.494%, and PC3 explained 11% of the variance (Table 8). Narsimha et al. (2018) [66] divided factor loadings into three categories: strong, moderate, and weak. These categories corresponded to the unconditional load values of >0.75, 0.75–0.50, and 0.50–0.30, respectively.

In all the seasons, Factor 1 exhibited a substantial positive loading of TDS, EC, and Cl^-. It is interesting to note that Sridharan and Nathan (2017) found elevated EC and TDS coupled with greater concentrations of ions like Cl^-, suggesting saltwater intrusion and other human-caused effects. Over the past ten years, the research has also observed a notable upward trend in EC, TDS, and Cl^- [67].

Factor 2 exhibited substantial positive loading of Ca^{2+} during Post-Monsoon and Monsoon seasons, indicating its critical role in the hydro chemical processes during these periods, as well as strong loadings of NO_3^- during Pre-Monsoon. The elevated levels of NO_3^- could be attributed to agricultural runoff and atmospheric deposition, which were more pronounced before the onset of monsoon rains. Factor 3 demonstrated a significant positive loading of F^- in the Pre-Monsoon season and Mg^{2+} in the monsoon season, respectively, suggesting a dynamic interplay between environmental conditions and ionic mobilization [68]. TDS was the most representative variable throughout the year, but NO_3^- in the Post-Monsoon, F^- in Pre-Monsoon, and Mg^{2+} in the monsoon seasons were the least representative variables.

Factor analysis of water quality parameters demonstrated notable seasonal fluctuations, with TDS serving as a reliable indicator across all seasons, underscoring its significance as a principal measure of water quality year-round. Elevated TDS levels can alter water palatability and may signify the presence of diverse dissolved minerals and salts. The differing impacts of NO_3^-, F^-, and Mg^{2+} emphasize the necessity for focused water quality management strategies that account for seasonal variations and potential pollution sources.

4. Conclusions

Between December 2022 and November 2023, groundwater samples were gathered in and around Koppal Taluk. According to APHA recommendations, the physical and chemical variables were examined along with cations and anions.

At every test location, EC was higher than the allowed levels in almost every season. Sampling stations KS-1, KS-7, and KS-8 had TDS values exceeding the permissible limit throughout the year; KS-1, KS-3, KS-7, KS-8, and KS-24 reported TH values more than the permissible limit during the Pre-Monsoon and Monsoon seasons. In all seasons, the concentration of calcium hardness was found to be more than permissible limits at KS-1, KS-2, KS-3, and KS-7. Magnesium hardness was found to exceed allowable limits at KS-1 throughout the year.

Table 8. Rotated component matrix of the three-factor model.

Variables	Monsoon			Pre-monsoon			Post-monsoon		
	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3
	Rotated Loadings Method by Varimax								
EC	0.760	0.393	0.495	0.756	0.493	0.414	0.051	0.944	-0.185
TDS	0.754	0.383	0.492	0.759	0.504	0.405	0.920	0.320	0.120
TH	0.458	0.770	0.428	0.803	0.532	0.226	0.947	0.266	-0.056
Ca	0.404	0.882	0.229	0.930	0.231	-0.017	0.510	0.779	-0.042
Mg	0.297	0.268	0.908	0.470	0.696	0.410	0.936	0.042	-0.059
Cl	0.678	0.541	0.457	0.694	0.581	0.337	0.963	0.096	0.093
F	0.884	0.290	0.256	0.086	0.242	0.937	0.328	0.489	0.527
SO_4	0.786	0.484	0.210	0.665	0.325	0.606	0.821	0.313	0.222
NO_3	0.814	0.465	0.279	0.336	0.841	0.229	-0.041	-0.249	0.874
Eigenvalues	7.611	0.549	0.481	7.084	0.923	0.409	5.356	1.484	0.990
% of the total variance	84.569	6.105	5.345	78.708	10.255	4.545	59.511	16.494	11.005
% of cumulative variance	84.569	90.674	96.019	78.708	88.963	93.509	59.511	76.005	87.010

Extraction method: Principal component analysis. Rotation method: Varimax with Kaiser Normalization. % - Percentage. Rotation converged in 5 Iterations.

In most seasons, the levels of nitrate and sulfate in groundwater samples at every sampling site remained within allowable bounds. In the Post-Monsoon season, fluoride levels peaked at KS-3 and KS-5 due to aquifer mineral dissolution and water pH. At KS-3, chloride levels peaked before the monsoon season.

Contrary to previous studies in similar regions, fluoride levels peaked at 2.02 ppm Post-Monsoon, exceeding Pre-Monsoon levels (0.74 ppm), indicating enhanced water-rock interaction. The observed Post-Monsoon elevation in calcium (816.00 ppm) suggested intensified recharge processes, which not only dissolved carbonate minerals but also enhanced cation exchange, a finding not previously reported in the study region. By identifying specific geochemical processes driving seasonal changes, this research provides a new framework for managing groundwater resources under seasonal and climatic influences.

The WQI is a valuable tool for decision-makers, enabling them to assess groundwater quality in a given water source and make informed decisions for better future use. Correlation analysis elucidated the relationships between parameters and identified various potential pollution sources, accounting for about 89% of the total variance. In summary, EC, TDS, total hardness, and cation values at KS-1, KS-2, KS-3, KS-7, and KS-8 exceeded permissible limits, which might be attributed to enhanced runoff and leaching processes that transport dissolved salts and nutrients from the surface soil layers to deeper strata. It is recommended that the habitats at KS-1, KS-2, KS-3, KS-7, and KS-8 utilize groundwater only after reducing the concentrations of the aforementioned physicochemical parameters and purifying the samples through techniques such as reverse osmosis (RO), ultraviolet (UV) treatment, coagulation, and flocculation. Furthermore, farmers in Koppal Taluk should consider using nitrogen fertilizers to enhance crop yields, monitoring soil salinity levels to prevent crop reduction, and implementing drip irrigation practices to minimize water loss and leaching, thereby improving crop quality.

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