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GIS-Based Mapping of the Water Quality and Geochemical Assessment of the Ionic Behavior in the Groundwater Aquifers of Middle Ganga Basin, Patna, India

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ABSTRACT

The study implemented Geographic Information System (GIS) techniques and multivariate hydrogeochemical analysis to evaluate the spatial-temporal and seasonal variation in the groundwater quality of Patna, India. For this purpose, sixty groundwater samples were collected and analyzed for major anions and cations during the pre-monsoon, monsoon, and post-monsoon seasons of 2019-2020. The physicochemical parameters such as pH, EC (Electrical Conductivity), TDS (Total Dissolved Solids), TH (Total Hardness), Ca^{2+}, Mg^{2+}, Na^{+}, K^{+}, HCO_3^{-}, Cl^{-}, SO_4^{2-} were considered to evaluate the water quality index. The result revealed degradation in groundwater quality from pre-monsoon (49.21) to post-monsoon (74.48). EC, TDS, TH, Mg^{2+}, Na^{+}, Ca^{2+}, K^{+} and HCO_3^{-} ions were found accountable for high WQI values at various sampling sites during different seasons. Spatial maps showed that 45 % of the sampling stations exhibited poor quality in all three seasons, where the eastern part of the studied region was revealed to be the most affected area. The application of multivariate statistical methods and hydrogeochemical investigation has clearly defined the dominant role of the weathering process, and reverse ion exchange mechanism in controlling the aquifer's ionic chemistry. Moreover, poor seepage system, and waste leachate from the surface have been found as the main cause of high levels of Na^{+}, K^{+}, and Cl^{-} in the eastern part of Patna.

INTRODUCTION

Groundwater is one of the most critical natural resources as it meets the domestic, agricultural, and industrial necessities and has an impact on the economic development of countries across the world (Li et al. 2018, Wu et al. 2020), especially in the arid and semi-arid regions (Li et al. 2018, Zhang et al. 2018, Adimalla et al. 2020). Nearly one-third of the global population relies on groundwater for drinking and domestic purposes, whereas it supplies 42% of the agricultural and 27% of the industrial demand worldwide (Nickson et al. 2005, Verma et al. 2020). However, the increasing demand for groundwater due to population explosion, coupled with the predicted water shortages, raises concerns about the sustainability of groundwater resources in meeting the future water needs of the world's population. By 2025, it is estimated that more than half of the world's population will be vulnerable to water shortages, while certain developing countries are projected to experience a shortfall of over 50% in water supply by 2030. In India, groundwater meets 85% of rural water supply, 62% of irrigational needs, and 45% of urban water consumption (Saha & Ray 2018, Verma et al. 2020). Increasing Population density, rapid urbanization, industrialization, and rising living standards have contributed to a continuous increase in water demands, which eventually led to unjudicial exploitation and deterioration in groundwater quality (Bodrud-Doza et al. 2020, Jha et al. 2020, Khan et al. 2020, Divya et al. 2023). Moreover, consumption of contaminated groundwater poses health risks associated with mortality and morbidity to humans and other living organisms (Bodrud-Doza et al. 2019, Kadam et al. 2019, Li & Wu 2019, Mgbenu & Egbueri 2019, Zhu et al. 2019, Bulut et al. 2020, Sulaiman et al. 2023a, Sulaiman et al. 2024). In 2017, contaminated water caused 1.2 million fatalities worldwide, with 569,679 deaths reported in India (Ritchie & Roser 2019). Bihar had a disproportionately high share of these deaths, accounting for 11.97% compared to the national average of 7.65%. (The Times of India 2018).

Patna, the state capital and largest city of Bihar has also experienced a drop in groundwater quality because of the city's uncontrolled growth, an antiquated and unrepaired water supply network, a poor drainage system, and overexploitation of groundwater sources (CDP PATNA 2010, UDHD 2016). According to the report published in Block-wise Ground Water Resources Assessment (2017), 50% of the blocks of Patna agglomeration are categorized as critical, 25% are overexploited, and only 25% are safe. Several researchers reported that groundwater quality is deteriorating at an alarming rate (Egbueri 2018, Egbueri & Unigwe 2019). Therefore, groundwater quality assessment is essential for knowing its suitability for domestic uses. Physico-chemical parameters are useful indicators of water quality, as they provide information on various physical and chemical characteristics of water, such as pH, EC, TDS, cations, anions, and levels of nutrients. However, these parameters alone may not provide a complete picture of water quality, as acceptable limits for each may vary. Water quality index (WQI) is a tool that combines multiple parameters into a single value to assess overall water quality. It takes into account the concentrations of different parameters and provides an easy-to-understand rating system for water quality (Horton 1965, Liou et al. 2004, Boyacioglu 2007). Numerous studies based on WQI approaches have been conducted globally (Boateng et al. 2016, Khosravi et al. 2017, Kawo & Karuppannan 2018, Khan & Rehman 2018, Karakuş 2019, Molekoa et al. 2019) and in India (Khan & Jhariya 2017, Acharya et al. 2018, Deepa & Venkateswaran 2018, Prasad Chourasia 2018, Gaikwad et al. 2020) validating its effectiveness in water quality assessment.

Moreover, combining the knowledge of traditional index systems with geospatial and hydrogeochemical mapping will certainly enhance the quality of assessment. GIS, or Geographic Information System, is a powerful tool used for analyzing, visualizing, and managing spatial data. It provides a platform for storing and retrieving huge amounts of data, which can be spatially linked to generate the necessary output for spatial analysis and integration. This feature of GIS makes it an important tool for solving water resource concerns, evaluating water quality, and assessing groundwater vulnerability. Besides, hydrogeological study can provide us information about the origin of the contaminants, or any spatial-temporal change in the chemical composition. Many authors have combined WQI with Geographic Information System (GIS) for assessing and depicting groundwater quality (Tiwari et al. 2017, 2018, Chakraborty et al. 2021, Chaurasia et al. 2021, Makki et al. 2021), but no previous work in such context has been conducted for Patna. Kumar et al. (2023a) and Sulaiman et al. (2023b) conducted a study to determine the geochemical processes controlling groundwater quality using multivariate approaches at Patna but did not put any emphasis on the water quality, its spatial and seasonal variation in their studies. Other studies conducted in Patna were based on physico-chemical analysis and WQI assessment and irrigation suitability but did not mention the root cause of the deterioration of groundwater quality (Zafar et al. 2022, Praveen & Roy 2021, Sukumaran et al. 2015). Therefore, the present study aims to fill this knowledge gap by employing a combined approach of WQI, GIS, and hydrogeology to provide a detailed account of groundwater status in Patna, which can provide valuable insights for developing effective conservation strategies and sustainable management practices for groundwater resources in Patna.

MATERIALS AND METHODS

Study Area

The present study is carried out in and around Patna, situated in South Bihar alluvial plains (latitude 25º13'and 25º45'N, longitude 84º43' and 86º44' E) with an area of 3172 Sq.km (Fig. 1). It is defined by the heavy deposition of Tertiary and Quaternary alluvial sediment, sourced from the Himalaya (Valdiya 2016). This district experiences a subtropical climate with hot summer and cold winter, and temperatures vary from 30°C to 43°C during summer and 5°C to 21.4°C during winter. The mean annual rainfall is around 1076 mm, and relative humidity reaches approximately 100% during summer (Sulaiman et al. 2021). The groundwater aquifer at Patna is under semi-confined conditions (Singh & Mishra 2012). A total of 85 deep tube wells dug by Patna Municipal Corporation and many shallow tube wells drilled by households extract groundwater daily from these aquifers (UDHD 2016). The current water demand for the Patna Planning area is 961 MLD (Million Liter Per Day), projected to increase by 452 MLD by 2031 (UDHD 2016). Groundwater resources have been preferred over surface water resources for a long time at Patna as the water of both River Ganga and Sone is unfit for drinking and requires extensive treatment before use.

Sample Collection and Analysis

In the present study, 60 borewell samples were collected seasonally in the month of March-April (pre-monsoon), August-September (monsoon), and October-November (post-monsoon) from 20 different sampling sites during 2019-2020. Sampling was done following the procedure prescribed by (APHA, AWWA, WEF 2012). Physico-chemical parameters like pH, EC, TDS, TH, Ca^{2+}, Mg^{2+}, Na^+, K^+, HCO_3^-, Cl^-, and SO_4^{2-} were analyzed following standard methods (APHA, AWWA, WEF 2012) and compared with (BIS 2012) standards. This study's statistical analysis is performed using SPSS version 22.0, XL STAT, and MS Excel 2019. A graphical representative of the dominant geochemical process and hydrogeochemical facie has been constructed using Grapher 14.0 software. ArcGIS 10.5 software is used to restrict the boundaries of Patna and all spatial distribution maps of WQI using the inverse distance weighted (IDW) interpolation technique.

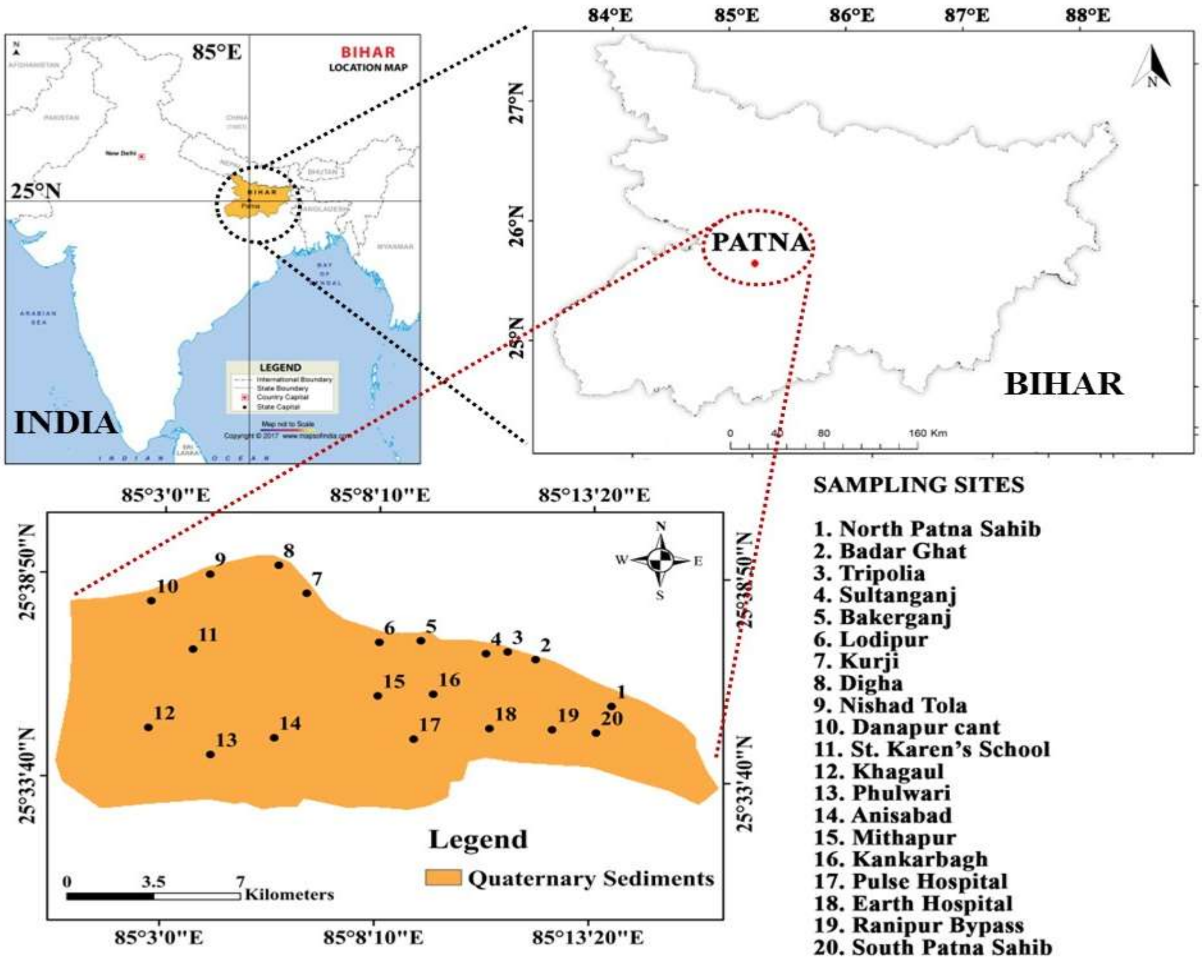

Fig. 1: Map showing the study area with 20 sampling locations.

Evaluation of the Water Quality Index

WQI is an effective tool that appraises water quality by combining the effect of different Physicochemical parameters into a single numeric value (Abtahi et al. 2015, Li et al. 2016, Iticescu et al. 2019). pH, EC, TDS, TH, Ca^{2+}, Mg^{2+}, Na^{+}, K^{+}, TA, Cl^{-}, SO_4^{2-} were considered along with (BIS 2012) standards to evaluate the water quality index. In the current study, WQI was estimated by the Weighted Arithmetic Index method (WAWQI) using the equation (1) developed by (Tiwari & Mishra 1985):

$$\mathrm{WQI} = \frac{\Sigma W_n \times Q_n}{\Sigma W_n} \quad \ldots(1)$$

Where W_n is the relative unit weight of the n^{th} water quality parameter, and Q_n is the quality rating of the n^{th} water quality parameter. The relative unit weight (W_n) and quality rating (Q_n) for each parameter can be calculated using the following expression given as equations (2) and (3), respectively.

$$W_n = \frac{K}{V_s} \quad \ldots(2)$$

Where K is the constant of proportionality, and it is calculated using the equation $K = 1/\sum 1/V_s$.

$$Q_n = \left[\frac{(V_n - V_i)}{(V_s - V_i)}\right] \times 100 \quad \ldots(3)$$

Where V_n is the value of the respective physico-chemical parameter obtained after analysis, V_i is the ideal parameter value, and $V_i = 0$ for all other parameters except for pH ($V_i = 7$). V_s is the standard permissible value for the n^{th} water quality parameter. The computation of relative weight and WQI for S1 during PRM is summarized in Table 1.

Multivariate Statistical Analysis

Two of the most used statistical methods, Principal component analysis (PCA) and Hierarchical cluster analysis (HCA) have been performed using SPSS version 22.0. The

Table 1: Calculation of WQI value for S1 sampling site during Pre-monsoon.

Chemical Parameters	V_s	$1/V_S$	W_n	V_n	Q_n	W_n X Q_n
pH	8.5	0.117647	0.427838	7.7	46.66	19.96292
EC	750	0.001333	0.004849	600	80	0.387906
TH	200	0.005	0.018183	245	122.5	2.227432
Ca^{2+}	75	0.013333	0.048488	61	81.333333	3.943716
Mg^{2+}	30	0.033333	0.121221	22	73.333333	8.889523
HCO_3^-	200	0.005	0.018183	296	148	2.691101
TDS	500	0.002	0.007273	326	65.2	0.474216
Na^+	200	0.005	0.018183	98	49	0.890973
K^+	12	0.083333	0.303052	10.4	86.666667	26.2645
Cl^-	250	0.004	0.014546	28	11.2	0.162921
SO_4^{2-}	200	0.005	0.018183	20	10	0.181831
	$\sum 1/V_s =$	0.27498			$\sum W_n$ X Q_n =	66.07704
	K=	3.636623				

Note: Unit in mg/L, Except EC (µS/cm) and pH.

principal component analysis is a form of factor analysis that reduces the dimensionality of large inter-correlated variables and attempts to explain the association and variance between them (Marghadhe et al. 2015, Barzegar et al. 2017). The outcome of the PCA is a simplified data set extracted from the linear combination of the variables from the original matrix as a new set of composite variables or Principal components (PC). Eigenvalue > 1 has been selected widely as a criterion for selecting representative Principal factors (Kaiser 1958). The study uses the varimax method for the orthogonal rotation of the original variables, which maximizes the variance of the rotated axes (Al-Qudah et al. 2011, Kaur et al. 2019). Factor loading of individual parameters is expressed as a numeric score that specifies the contribution of each variable along that principal axis. Factor loading of variables having a value >0.5 was considered significant for result interpretation. Further, validation of factor analysis was done using Hierarchical cluster analysis, which group data sets with underlying similarities. The study uses the widely accepted Ward's method, in combination with squared Euclidean distance for clustering variables, as it tends to maximize the homogeneity between two variables in such a way that the distance between them represents the difference between their observed value (Bhuiyan et al. 2011, Kumar 2019).

GIS Mapping

The IDW interpolation technique was employed in conducting a spatial analysis of the Water Quality Index (WQI) using ArcGIS version 10.5. Inverse Distance Weighting (IDW) is an interpolation technique commonly used in Geographic Information Systems (GIS) to estimate values of a variable at unsampled locations based on known values at surrounding sample locations (Gunarathna et al. 2016). The technique assumes that the surrounding sample locations influence the values at unsampled locations, and the influence decreases with distance from each sample location (Gnanachandrasamy et al. 2015). IDW is widely used due to its user-friendliness, computational efficiency, and ability to accommodate outliers, resulting in highly accurate results (Zafar et al. 2022).

RESULTS AND DISCUSSION

Analytical Results

Table 2 represents the physicochemical characteristics and comparative analysis range with Bureau of Indian Standards limits (BIS 2012). The values of pH, Cl^-, and SO_4^{2-} were within the desirable limits. The concentration of EC and TDS ranges from 300 to 1700 µS/cm and 236 to 1195 mg/L, and 31.66% have high EC and TDS exceeding BIS standard guidelines. More dissolved salts caused the elevated EC level in the water (Panghal & Bhateria 2020, Sarker et al. 2020, Narasaiah & Rao 2021). Several researchers reported that a high concentration of EC and TDS might be due to soil mineralization and increasing ionic activity in groundwater aquifers (Adimalla 2019, Chegbeleh et al. 2020). HCO_3^- is the most dominant among the anions, followed by Cl^- >

Table 2: Summary of the physico-chemical parameters and its comparison with (BIS 2012) Standard during 2019-2020.

Parameters	PRM (Range)	MON (Range)	POM (RangE)	Annual Avg. ± STD	BIS (2012) Acceptable Limit	% Sample Exceeding BIS standards
pH	7.3-8.1	7.1-7.8	7.1-7.7	7.39 ± 0.18	8.5	0
EC (μS/cm)	300-1300	400-1400	500-1700	722.5 ± 277.79	750	30
TH [mg.L^{-1}]	207-575	158-418	204-554	287.45 ± 79.10	200	100
Ca^{2+}[mg.L^{-1}]	61-149	17.63-72.48	34.46-165.93	66.59 ± 19.88	75	25
Mg^{2+}[mg.L^{-1}]	3-44	14.12-81.81	16.07-66.23	29.15 ± 11.79	30	30
TDS [mg.L^{-1}]	236-995	262-1188	279-1195	462.70 ± 223.65	200	35
Na^+ [mg.L^{-1}]	43-125	43.1-102.4	43.3-236	69.99 ± 20.74	500	0
K^+ [mg.L^{-1}]	3-10.4	4.6-79	5.8-126	10.6 ± 9.86	200	15
HCO_3^- [mg.L^{-1}]	260-388	250-456	228-426	307.15 ± 40.38	12	100
Cl^- [mg.L^{-1}]	8-167	7-161	11-169	50.53 ± 44.05	250	0
SO_4^{2-} [mg.L^{-1}]	3-69	1-92.2	10.2-113.8	35.29 ± 28.11	200	0

SO_4^{2-}, and all the samples have HCO_3^- above BIS guidelines. Increased bicarbonate ion concentration is attributed to the carbonate and silicate weathering process (Alaya et al. 2014, Narsimha & Sudarshan 2017, Roy et al. 2018, Srivastava & Parimal 2020, Divya et al. 2023). (He et al. 2021) reported that a high concentration of HCO_3^- in groundwater might be due to the water-soil interactions and degradation of organic matter. The cations concentration is found as Ca^{2+}> Na^+ >Mg^{2+}>K^+ during pre-monsoon and post-monsoon whereas Mg^{2+} Na^+> Ca^{2+}>K^+ in monsoon season. In total, 36.66% and 25% of groundwater samples have high Mg^{2+} and Ca^{2+}. A high concentration of Mg^{2+} and Ca^{2+} with HCO_3^- determines the hardness of groundwater. The total hardness value in 88.33% of collected samples exceeds the BIS guidelines for drinking. Increased TH levels could be related to calcite and dolomite minerals and their subsequent leaching into the groundwater (Sharma et al. 2017, Adimalla & Venkatayogi 2018, Sampson et al. 2020).

Water Quality Index

WQI was calculated seasonally using the Weighted Arithmetic Water Quality Index method (Horton 1965) for all sampling locations during 2019-2020. Classification of groundwater based on WQI values is shown in (Table 3, Fig. 3). Averaged WQI varied from 49.21 in pre-monsoon, 51.54 in monsoon, and 74.48 during post-monsoon seasons, revealing a decline in water quality from pre-monsoon to post-monsoon. A deteriorated WQI value during post-monsoon in the study area is due to an elevated EC, TDS, Mg^{2+}, $Na^{+,}$ and K^+ ion (Krishna Kumar et al. 2015, Chaudhry & Sachdeva 2020, Mahmud et al. 2020). Similar trends were reported from some other regions of the Indo-Gangetic Plains (Verma et al. 2018, Palmajumder et al. 2021). A study conducted by (Balamurugan et al. 2020) in Tamil Nadu also revealed the deterioration of WQI value during the post-monsoon period. Groundwater quality degradation during the monsoon and post-monsoon season can be attributed to increased solute concentration in the groundwater as water seeps down through the vadose zone (Subba Rao 2008, Manikandan et al. 2020). Shukla & Saxena (2020) reported contrasting results from the Raebareli district of the neighboring state of Uttar Pradesh, where 57% of samples fall in the poor category during pre-monsoon whereas 43% during monsoon and post-monsoon. The spatial variation map of WQI showed that water quality was poor in most of the eastern (S1, S2, S3, S4, S6, S16, S20) and south-western portion of the study area (S11, S12, S13) during the pre-monsoon (Fig 2. a) whereas during monsoon majority of study area falls in poor category except small patches of northern (S5, S7, S8, S9, S10) and central (S15, S18) regions (Fig 2. b). During post-monsoon, a major portion of the study area falls in poor water quality, where S10 and S19 fall in good, S3 is very poor, and S20 is in the unsuitable category (Fig 2. c). Similar trends were reported from some other regions of the Indo-Gangetic Plains (Verma et al. 2018, Palmajumder et al. 2021). Shukla & Saxena (2020) reported contrasting results from the Raebareli district of the neighboring state of Uttar Pradesh, where 57% of samples fall in the poor category during pre-monsoon whereas 43% during monsoon and post-monsoon. Another study conducted by (Balamurugan et al. 2020) in Tamil Nadu also revealed the deterioration of WQI value during the post-monsoon period. Groundwater quality degradation during the monsoon and post-monsoon season can be attributed to increased solute concentration in the groundwater as water seeps down through the vadose zone (Subba Rao 2008, Manikandan et al. 2020). Fig. 3 represents a line graph that summarizes the overall WQI

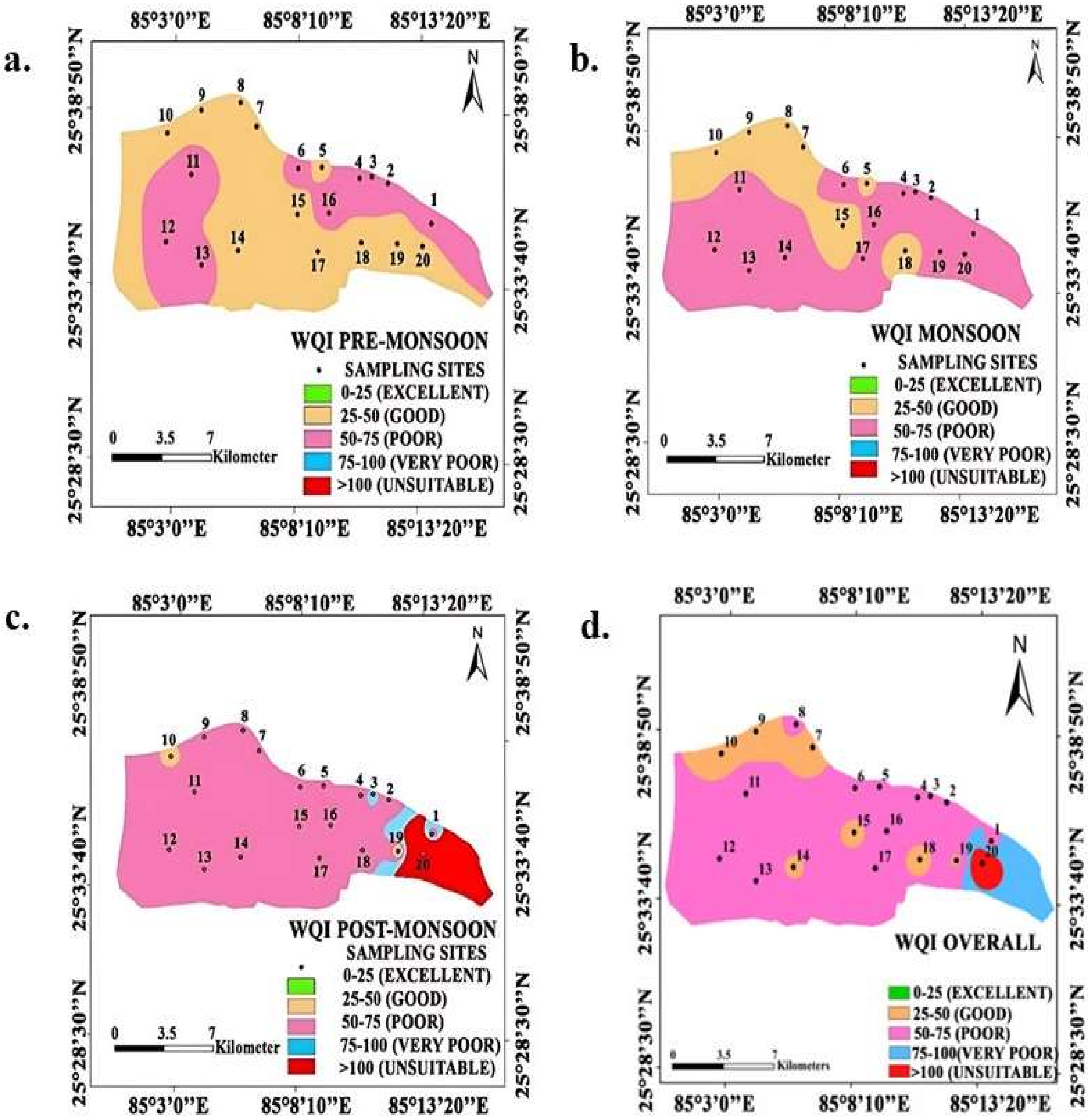

Fig. 2: Spatial maps showing variation in WQI values during (a) pre-monsoon, (b) monsoon, (c) post-monsoon.

of the sampling sites. Line graph showed that S1, S2, S3, S4, S5, S6, S8, S11, S12, S13, S16, S17 fall in poor water quality whereas S7, S9, S10, S14, S15, S18, S19 falls in good water category and S20 falls in unsuitable for drinking purposes.

Hydro-Geochemical Investigation for the Quality Deterioration

Water type and weathering process: The lithological framework, solute kinetics, and flow pattern through the groundwater aquifer are combinedly described as a function of hydrogeochemical facie. It is used to elucidate information about the water type and hydrogeochemical process controlling the ionic composition of the study area (Ali & Ali 2018, Singh et al. 2020). Durov (1948) proposed a diagram with one central rectangular plot at the base of two separate ternary plots. The point in the rectangular plot falling in a particular grid represents the intersection of cationic and anionic values from their respective ternary plots (Chadha 1999). Nearly 20% of samples plotted in field 5 denote water

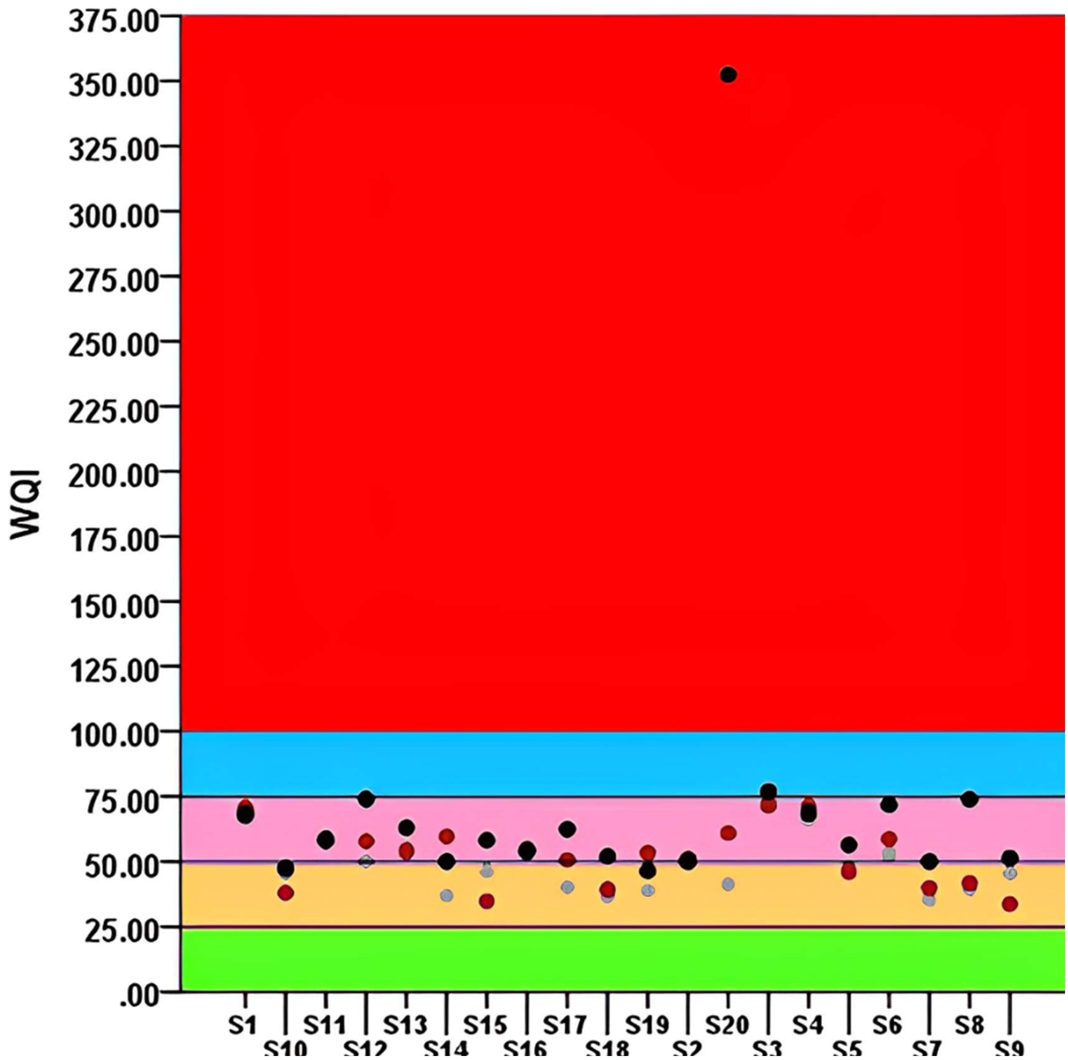

Fig. 3: Scatter plot of WQI value during different seasons in the study area.

with no dominant cations and anions. The samples that were plotted in field 5 include S3, S4, S19, and S20, which in the above discussions have marked with a higher value of total dissolved solids. Several studies have concluded similar findings and suggested infiltration of recent freshwater has caused the simple dissolution of these ions in the studied area (Singh et al. 2020, Das et al. 2021, Kumar et al. 2019). The dominant hydrogeochemical facie in the groundwater of the study area was revealed to be Mg-HCO_3 water type, with ~80% of samples falling in field 6 (Fig. 4). The influence of silicate weathering might be the reason behind the surplus of HCO_3^- ion. In contrast, mineral dissolution of carbonate rocks and reverse ion exchange processes caused an elevation in the level of Mg^{2+} ions in the study area (Saha 2019). The outcome of the Durov diagram further explains the geogenic input of divalent ions has contributed to an increase in the conductivity and hardness of the groundwater samples, whereas anthropogenic source has led to a remarkable rise in Na^+ and K^+ levels in the eastern side of the study area.

The rock water interaction, weathering process, climatic conditions, and residence time of groundwater in the aquifer of the catchment area primarily control the geo-chemistry of groundwater. The ionic composition of the groundwater is dependent on the types of minerals and rocks that it has encountered during this percolation process. Many researchers have employed bivariate ion scatter plots to investigate the dominant rock weathering process, and any deviation from the general trend might signify the presence of anthropogenic disturbances (Kumar et al. 2022, Sulaiman et al. 2023c, Kumar et al. 2023b). The position of a groundwater sample in a $Ca^{2+} + Mg^{2+}$ versus $HCO_3 + SO_4^{2-}$ plot provides

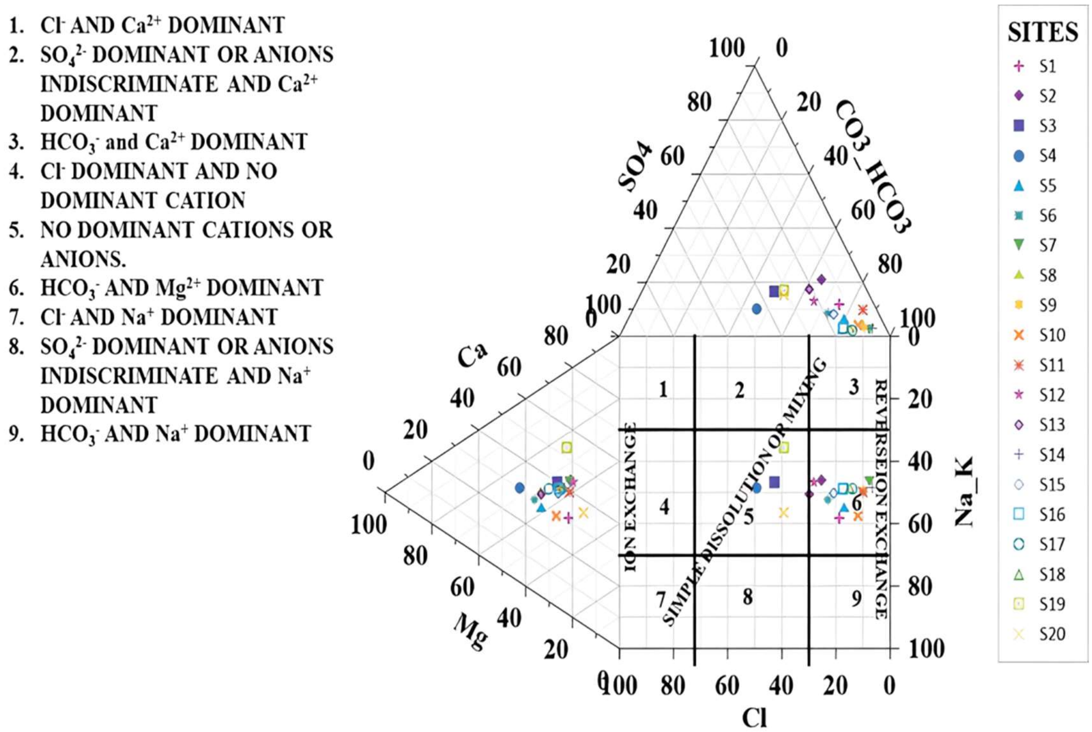

Fig. 4: Durov diagram denoting major hydrogeochemical facie and process controlling the solute chemistry in the groundwater of Patna.

insights into the weathering processes in the studied region. Groundwater samples falling above the euiline (1:1) in the plot suggest high concentrations of Ca^{2+} and Mg^{2+} ions, which are associated with the dissolution of carbonate rocks, and the prevalence of reverse ion exchange processes.

In contrast, samples located below the euiline (1:1) are characterized by lower concentrations of Ca^{2+} and Mg^{2+} ions, where the input of HCO^3 is associated with silicate weathering and ion exchange processes. Most of the groundwater samples lay near or below the 1:1 equiline, suggesting the prevalence of silicate weathering, with substantial input from carbonate rocks to the groundwater aquifer (Fig. 5a). Thereafter, the samples in the $Ca^{2+} + Mg^{2+}$ versus total cation (TZ^+) scatter plot were situated around $0.5TZ^+$ equiline, validates the involvement of silicate rocks, or cal-silicate minerals (amphiboles, pyroxene, plagioclase) in making the ionic composition of the studied area (Fig. 5b). The bivariate plot of $Na^+ + K^+$ against total cations (TZ^+), deciphers the input of $Na^+ + K^+$ ion in the groundwater aquifer. The samples plotted near or above the 0.5 TZ^+ marked the role of silicate weathering in contributing the monovalent ions to the groundwater, whereas deviation from the $0.5TZ^+$ equiline suggests some anthropogenic agricultural or seepage leaching. The results further affirm the involvement of the silicate weathering process as the majority of the studied region has spread near the $0.5TZ^+$ equiline (Fig. 5c). However, sites S3, S4, S19 showed a notable deviation from the $0.5TZ^+$ equiline, which signifies the presence of reverse ion exchange process that has elevated the level of divalent ion in these sites.

Interestingly, site 20 was noted with the highest cationic budget, where excess of $Na^+ + K^+$, might be a consequence of some anthropogenic activities. As there are no such agricultural activities marked on the sites, abrupt increases in Na^+ and K^+ might be due to poor seepage systems and sewage infiltrations. The same has been investigated by plotting Cl/(HCO_3+SO_4) against $Na^+ + K^+$ (Fig. 5d). In the absence of any geogenic source, a high value of Cl-indicates the sewage, domestic, and animal waste infiltration (Zafar et al. 2022). The result revealed a good correlation of r^2=0.524 between the two variables of interest, suggesting the role of mineral dissolution in contributing Cl^- and Na^+ to the groundwater. A higher value of Cl^- ion was noted at sites S3, S4, S19, and S20, where increasing value $Na^+ + K^+$ at S20, S3, and S4 suggests a similar source of these ions, such as poor seepage system and waste leachate from the cattle corralled in the household in the groundwater at the respective sites.

Principal component analysis: The KMO (Kaiser-Meyer-Olkin) value was found to be 0.641, which suggests the data set is relevant for factor analysis (Eyduran et al. 2010). A substantially greater value of Bartlett's sphericity test (χ^2=388.383) than the critical value (χ^2=85.965) at 'degree

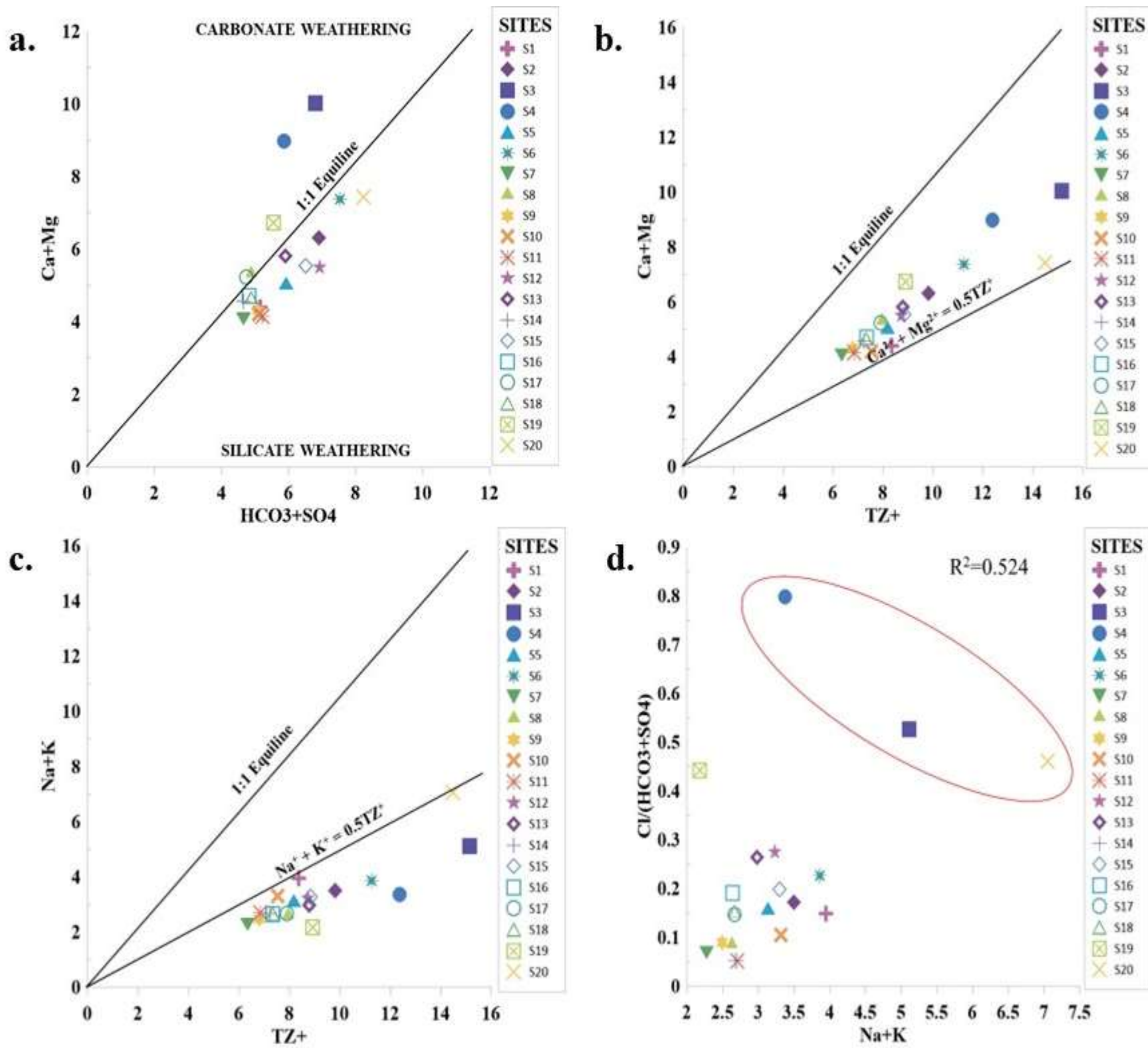

Fig. 5: Bivariate ion scatter plots identifying ionic relationships between different variables.

of freedom' 66 and significance level 0.05 revealed that the test has significantly reduced the dimensionality of the original data (Kumar et al. 2018, Kumar et al. 2019). After that, PCA was performed for the obtained data set using varimax rotation in XL-STAT to evaluate the effect of each WQV on their respective principal factor in a PCA. The two principal factors having eigenvalue >1 that cover the cumulative variance of 78.25% were considered significant for further interpretation (Kim & Mueller 1978) (Fig. 6a). According to (Liu et al. 2003), loading values >0.75 signifies "strong," between 0.5 - 0.75 considered as "moderate" and "weak" when lies between 0.3 to 0.5. The water quality variable with high factor loading along Principal Factor 1 include TH (0.962), TDS (0.897), EC (0.869), Cl^- (0.887), Mg^{2+} (0.842) and Ca^{2+} (0.745) (Table. 3). The high value of EC, TDS, and TH in the first factor might be due to the high loading of Ca^{2+}, Mg^{2+}, and Cl^- leading to increased hardness and conductivity (Kaur et al. 2019). The dominance of Ca^{2+} and Mg^{2+} (cations), along with principal factor 1, also indicates the presence of rock weathering or reverse ion exchange process (Subramani et al. 2010). A low factor loading of WQI in component 1 is attributable to the high factor loading of the mentioned variable. It signifies that any decrease in the value of those variables in the first factor tends to increase the factor loading of WQI (Mohammadpour et al. 2016), which is evident in the Principal Factor 2 matrix. Principal Factor 2 was observed to have a % variance of 15.03 and is characterized by a high factor loading of monovalent cation K^+ (.958) and Na^+ (.809), suggesting the presence of anthropogenic influence (Singh et al. 2019, Kaur et al. 2019) (Table 3). The result obtained for principal factor 2 suggests the influence of the silicate weathering process and

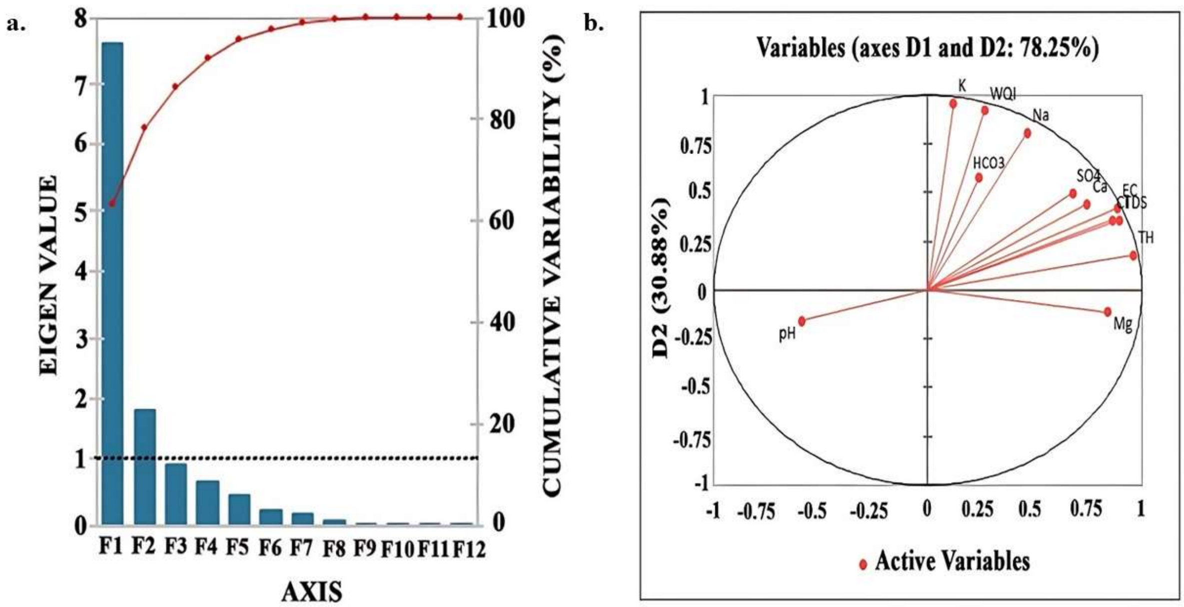

Fig. 6a: Scree plot showing principal factors and their eigenvalue together with cumulative variability **b.** Score plot showing positive and negative factor loading in groundwater at Patna.

reverse ion exchange process in the study area playing a significant role in lowering the concentration of Mg^{2+} (-0.113) and Ca^{2+} (.441) (Srinivasamoorthy et al. 2014) and thereby increasing the factor loading of WQI (0.920) in Principal factor 2.

Hierarchical cluster analysis (HCA): Hierarchical Cluster Analysis has been performed to categorize the primary group of water quality variables, which are alike and most probably originated from similar sources. The hierarchical tree of water parameters exhibited two distinct clusters, as shown in Fig. 7. Cluster 1 showed a very strong association between electrical conductivity (EC), total hardness (TH), and total dissolved solids (TDS). The ions that contribute to a relatively high value of hardness and TDS include Cl^-, Ca^{2+}, SO_4^{2-}, and Mg^{2+}. Moreover, the clustering of these variables together suggests the geogenic dissolution of rocks into the groundwater aquifer. A similar observation is also seen in the case of factor analysis discussed above. A strong association between K^+ and WQI shows a significant contribution of K^+ ions in deteriorating water quality, followed by Na^+, as depicted in cluster 2. A close association of Na^+ with HCO_3^- in cluster 2 marked the role of the silicate weathering process in the higher concentration of HCO_3 ion in the groundwater. The two separate clusters suggest each parameter's role in determining the water quality of the study area.

Table 3: Factor loading after Varimax rotation.

	D1	D2
pH	-0.59	-0.158
EC	**0.887**	0.422
TH	**0.962**	0.181
Ca^{2+}	**0.745**	0.441
Mg^{2+}	**0.842**	-0.113
TDS	**0.897**	0.359
Na	0.465	**0.809**
K	0.118	**0.958**
HCO_3^-	0.24	0.581
Cl^-	**0.861**	0.359
SO_4^{2-}	**0.677**	0.498
WQI	0.265	**0.92**

CONCLUSION

The present study investigated the current groundwater status of Patna, Bihar, for domestic purposes using traditional WQI methods (WAWQI) as well as modern (Geographical Information System and multivariate geochemical investigations) methods. The study area was marked with similar ionic composition throughout the sampling stations and seasons, where Mg-HCO_3 water type and reverse ion exchange process dominated the water chemistry. The seasonal impact was very evident with the deterioration of water quality in the post-monsoon season. The spatial analysis revealed comparatively higher WQI values in the northeastern region of Patna in nearly all seasons. The operative application of

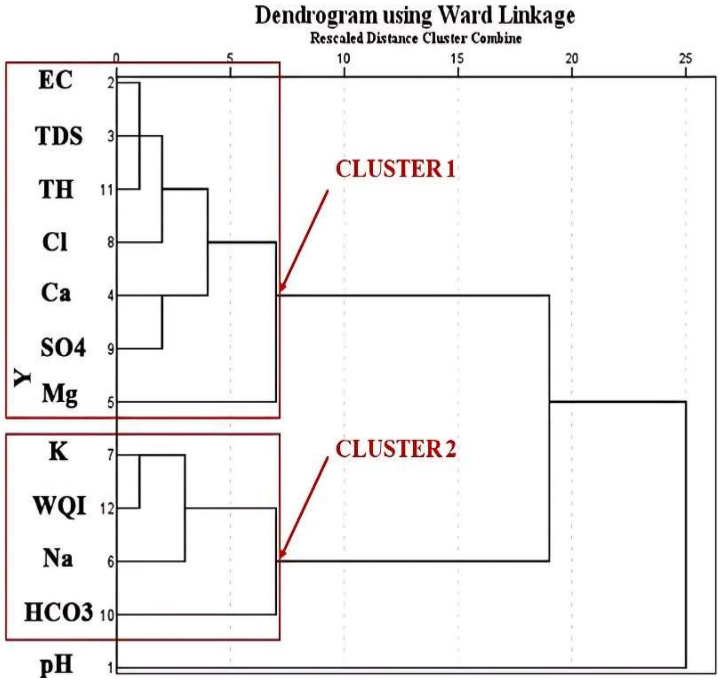

Fig. 7: Dendrogram showing homogeneity between different water quality variables of the groundwater in Patna.

multivariate techniques in the source identification of ionic constituents is further documented in the study. It discusses the role of Na^+ and K^+ in water quality deterioration in the northeastern part, which revealed high factor loading of (0.809), (0.958), $Na^{+,}$ and K^+ in the principal factor 2. The study provides a very pioneer and comprehensive insight into the water quality status in areas where such work has not been documented before, which assesses the water quality index using the GIS approach and multivariate techniques. Moreover, the future perspectives for assessing water quality index using the GIS approach and multivariate techniques are promising, and this approach is likely to become an essential tool for water resources management and decision-making. By providing a more comprehensive understanding of the spatial and temporal variations of water quality, it can help support sustainable water use, protect public health, and preserve groundwater.

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