Evaluation of groundwater quality in West Tripura, Northeast India, through combined application of water quality index and multivariate statistical techniques

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Abstract

Groundwater is one of the major resources of civilization which cannot be visualized directly in day to day life. Scarcity of groundwater is an alarming threat to the ecosystem. The present study was conducted to evaluate water quality and interrelated environmental impact of 38 groundwater samples applying the water quality index (WQI) method and multivariate statistical tools. This investigation includes some techniques like weighted arithmetic and entropy weight WQI, principal component analysis (PCA), correlation analysis (r), cluster analysis (CA), and spatial mapping. The data required for these tools were used after the estimation of physicochemical parameters of each sample. Calculated WQI values identified iron (Fe) followed by turbidity and dissolved oxygen (DO) as the most influencing parameters for non-potability of groundwater samples. Fe contamination in 34 samples exceeded WHO standard limit (0.3–1 mg/L) and the maximum value was recorded as 15.23 mg/L. Findings of correlation matrix (r) suggest all ions have a common source and geochemical processes. Outcomes of PCA followed by a scree plot diagram extracted three major factors with a total variance of 84.5% clarifying the explanations behind water quality deterioration. Based on data ranges of all parameters, the spatial distribution map has been procured following the methods for identification and management. CA investigated three major groups using Ward's method of either sampling locations or analyzed parameters and showing through dendrogram plots. Considering all the above, it is suggested that physicochemical parameters should be monitored periodically to preserve water resources and provide emphasis on management practices to maintain water quality.

Keywords Water quality index · Spatial distribution map · Correlation coefficient · Principal component analysis · Cluster analysis · Dendrogram

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Introduction

Groundwater is a vital and sustainable natural resource for socio-economic development, for healthy ecosystems, and for improving the productivity and welfare of populations. Leaching action of minerals, extreme utilization of manures, and anthropogenic activities (Rango et al. 2012) make groundwater non-potable because these activities enhance contamination of mainly heavy metals (arsenic (As), Fe, cadmium (Cd), chromium, and fluoride (F^-)) in groundwater. The concentration of these harmful toxic pollutants is rising continuously due to rapid population growth, economic activity, infrastructure development, and industrialization (Ram et al. 2021). The long-term viability of groundwater quality is among the most significant challenges facing

the world today (Mittal et al. 2021). In dry period, the situation becomes more critical because of low groundwater level.

Water contamination deteriorates water quality resulting in an adverse impact on aquatic life, human health, economic development, and social thriving (Milovanovic 2007). Therefore, we need to stop water pollution (Simeonov et al. 2003) sourced from anthropogenic activities by imposing rules and regulations designed by the policymakers of every country regularly (Vasanthavigar et al. 2010). Before applying several treatment options like physicochemical methods and membrane technology for groundwater purification, its quality should be monitored and maintained. Water quality index (WQI), used by the scientific community and decision-makers (Abbasnia et al. 2019; Adimalla 2021; Chaurasia et al. 2018; El Baba et al. 2020; El Osta et al. 2020; Panghal and Bhateria 2020; Ram et al. 2021), is a technique which combines multiple parameters into a single numeric dimensionless value determined by integrating water quality variables according to their relevance (Mallick et al. 2021). This simple, outstanding and proficient tool is applied to classify groundwater quality for drinking into any one of five categorizes—excellent, good, medium, poor, and extremely poor. Many countries like India (Chaurasia et al. 2018; Panghal and Bhateria 2020), Iran (Abbasnia et al. 2019), Brazil (Sabino et al. 2020), and the UK (El Baba et al. 2020) applied WQI technique to confirm current scenario of groundwater.

Multivariate statistical analysis such as correlation analysis (r), principal component analysis (PCA), and cluster analysis (CA) elucidates the relationships between water quality variables and possible factors, as well as their influences on water quality responses (Kumar and Krishna 2021). Correlation coefficient (r), also known as Pearson correlation, reflects the relationship between at least two dependent and independent variables (Sadat-Noori et al. 2014). This concept is applied by various researchers (Awomeso et al. 2020; El Osta et al. 2020; Nath et al. 2021; Panghal and Bhateria 2020).

PCA is effectively used to elucidate large datasets in complex forms and to make less prejudiced processes (Kazi et al. 2009). It additionally encourages us to recognize the possible pollution sources or factors impacting water quality. Besides, PCA strategies have already been established to be a beneficial tool for water resource management and explanation of contamination issues (Awomeso et al. 2020; Kumar and Krishna 2021; Nyam et al. 2020). By classifying samples as per their distinct chemical properties, CA proves to be an effective tool for establishing chemical interactions between them (Sheikhi et al. 2021).

Published journals on groundwater quality in Tripura, northeastern state of India, are scanty. Singh and Kumar (2015) focused on the status of irrigation and drinking underground water quality in rural and urban areas of Agartala (state capital, Tripura) after analyzing 21 samples. Coexistence of As and F^- in 59% samples of groundwater in the Dharmanagar region, North Tripura, was established by Bhattacharya et al. (2020) through correlation coefficient data. As and F^- concentrations exceeded WHO permissible limits in 30% samples. Paul et al. (2019a) reported dominance of carbonate dissolution, rock–waterinteraction, and silicate weathering processes in groundwater hydrochemistry. Paul et al. (2019b) observed Fe and Mn in majority of samples exceeded BIS standard limit and all samples satisfy the irrigation suitability criterion. Brindha et al. (2020) found 66.2% of groundwater samples had good quality water by applying the Canadian Council of Ministers of the Environment Water Quality Index (CCMEWQI) method. They also observed a high risk to human health from groundwater ingestion containing unsafe levels of As and Fe.

Groundwater demands in Tripura meet 50% of irrigation needs, 50% of urban needs, and 80% of rural needs (Debbarman et al. 2013). The necessary actions to be made to ensure the present status of groundwater on regular basis due to changes in various parameters like (i) rapid population growth, (ii) anthropogenic activities, (iii) liquid effluents from industries and engineering workshops, (iv) contaminated water by agricultural waste and effluents, and (v) climatic situation of the environment. In this study, an effort has been initiated to achieve the following objectives: (i) to assess groundwater quality and environmental impact using numerical tools like WQI, correlation coefficient, PCA technique, spatial mapping, and CA; (ii) to generate experimental data for these tools through analysis of 38 groundwater samples collected in January, 2018, from both urban and rural areas of West Tripura District; and (iii) to obtain outcomes that help decision-makers in India, especially for the Tripura Government, for developing a suitable mechanism for treatment as well as making strategies for avoiding future contamination. Besides, an extensive literature survey revealed that a special attention on Fe contamination with its impact should be elaborately discussed.

Study area

The study area covers seven rural development blocks, two Nagar Panchayats of West Tripura District including the Agartala Municipal Corporation (Table 1; Fig. 1). Tripura is one of the smallest states which is located in the southern portion of Northeast India. Sub-tropical and high-humid climate with strong existence of

Table 1 Block/MunicipalCorporation/Nagar Panchayat wise sampling locations

Sample no	Sample locations	Latitude (°)	Longitude (°)	Block/Municipal Corporation/Nagar Panchayat
GW1	MBB College	23.8270	91.2969	Agartala Municipal Corporation
GW2	Golbazar Market	23.8265	91.2855	Agartala Municipal Corporation
GW3	Lake Chowmuhani	23.8419	91.2797	Agartala Municipal Corporation
GW4	Radhanagar Bus Stand	23.8449	91.2824	Agartala Municipal Corporation
GW5	AGMC	23.8603	91.2927	Agartala Municipal Corporation
GW6	Gurkhabasti	23.8554	91.2827	Agartala Municipal Corporation
GW13	Ushabazar	23.8861	91.2433	Agartala Municipal Corporation
GW14	Airport	23.8914	91.2438	Agartala Municipal Corporation
GW15	Narsinghgarh Bazar	23.9075	91.2487	Agartala Municipal Corporation
GW16	Barjala H.S. School	23.8636	91.2734	Agartala Municipal Corporation
GW17	Battala	23.8283	91.2671	Agartala Municipal Corporation
GW33	Women's College Agartala	23.8364	91.2854	Agartala Municipal Corporation
GW34	Bodhjung Girls School	23.8373	91.2895	Agartala Municipal Corporation
GW35	Chandrapur Bus Stand	23.8394	91.3066	Agartala Municipal Corporation
GW36	Kalyani Water Supply	23.8303	91.2966	Agartala Municipal Corporation
GW18	A.D. Nagar	23.8180	91.2715	Agartala Municipal Corporation
GW19	Arundhuti Nagar	23.8162	91.2493	Agartala Municipal Corporation
GW20	Hapania	23.7914	91.2660	Agartala Municipal Corporation
GW27	BhatiAvaynagar	23.8427	91.2705	Agartala Municipal Corporation
GW21	Jogendranagar	23.8084	91.3131	Dukli Block
GW22	Ananda Nagar	23.7859	91.3168	Dukli Block
GW23	14 Goddes Temple	23.8453	91.3435	Old Agartala Block
GW24	Banikya Chowmuhani	23.8619	91.3351	Old Agartala Block
GW25	Bodhjungnagar	23.8611	91.3348	Old Agartala Block
GW26	Ranirbazar	23.8375	91.3648	Ranirbazar Nagar Panchayat
GW10	Santipur, Lembucherra	23.9263	91.3277	Mohanpur Block
GW11	Kamalghat Bazar	23.9279	91.3348	Mohanpur Block
GW12	Fatikchhara	23.9529	91.3464	Mohanpur Block
GW29	Khumulung Park	23.7942	91.4397	Belbari Block
GW30	Jirania Bazar	23.8187	91.4389	Jirania Nagar Panchayat
GW28	Mohanpur, Majlishpur	23.8207	91.3920	Jirania Block
GW31	Champaknagar Bazar	23.8119	91.4700	Jirania Block
GW37	NITA Central Workshop	23.8417	91.4203	Jirania Block
GW38	H4B NITA faculty quarter	23.8425	91.4303	Jirania Block
GW32	Mandai (Forest Office)	23.8607	91.4797	Mandai Block
GW7	Salbagan	23.8917	91.2915	Bamutia Block
GW8	College of Fisheries	23.9035	91.3074	Bamutia Block
GW9	College of Agriculture	23.9138	91.3200	Lefunga Block

southwest monsoon is characterized with high rainfall in this region. The area receives about 2000 mm (average) annual rainfall and experiences three seasons (winter, summer, and rainy). Groundwater is mainly recharged by rainwater. The topography of the study area is characterized by hilly, undulating plains and alluvial valleys. Dendritic with sub-parallel to parallel drainage system is noticed (Fig. 1). A total 38 number of groundwater sampling locations are randomly selected in West Tripura District, mainly from in and around the Agartala City as well as from Gram Panchayats and Tripura Tribal Areas (ADC villages). The geographical extension of study area is bounded by longitudes between 91° 09′ E to 91° 47′ E and latitudes between
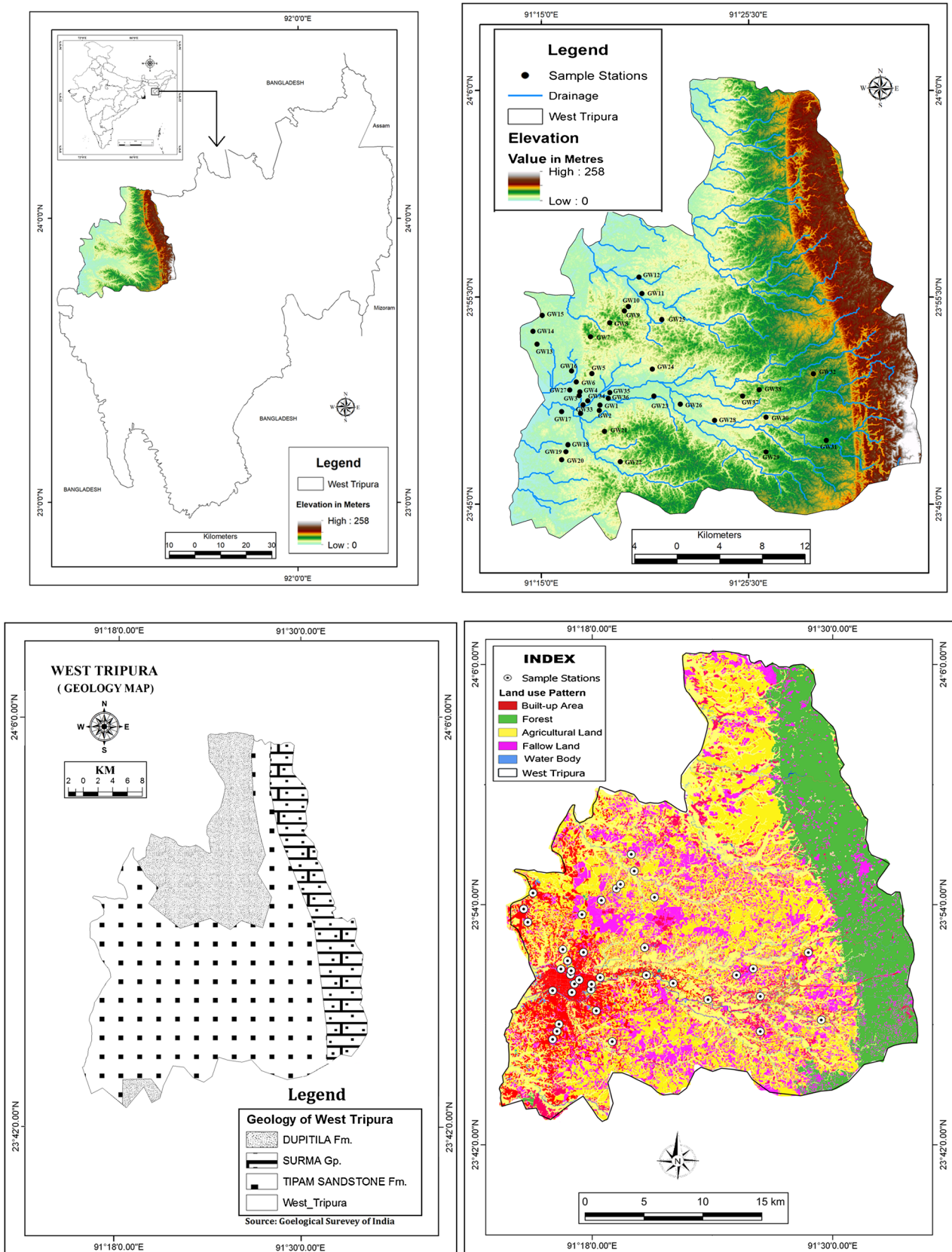
Fig. 1 Sampling locations of the study area

23° 16′ N to 24° 95′ N. All the samples are collected in HDPE bottles from tube wells as per standard protocols. The yield of tube wells varies from 50 to 200 LPM. About 18% samples have been collected from < 20 m depth while 53% samples have 20–40 m depth. Only about 29% of samples are collected from > 40 m depth which influences certain degree of geochemical zoning. The average maximum and minimum temperatures of the study area are experienced at 35 °C and 10 °C, respectively. The purpose behind selecting the study area expecting the groundwater might be exceptionally contaminated due to the following: (i) it is the highest populated (988,192 as per 2011 census of India) district covering 984 km^2; (ii) Agartala, district headquarters, as well as the state capital, is the primate city situated in this area; (iii) rubber and allied processing industries (ABM rubber industries and Malaya rub tech industries) are well-established; and (iv) geographically, it is bounded by Bangladesh (groundwater affected country) on the west.

Geological and hydro-geological setting in study area

Geologically, the study area is young. The massive fluvial sediments are periodically deposited and get uplifted due to the upliftment of whole landmass. The geology of the District has been sub-divided into four major groups: Surma, Tipam, Post Tipam, and Recent. Generally, sandstone, shale, and loose unconsolidated sand, silt, and clay are predominant in its structure (Dasgupta 1979). The area particularly represents the second-order landform system with an average altitude of 15 m. The erosion remnant mounds separated by linear in-filled valleys characterized this highly dissected terrain. These are locally referred to as tilla and lunga respectively.

The Quaternary arrangement, the most recent topographical timeframe in Earth's history, is made out of Alluvium sand/silt and clay alternating beds under rock group of "unconsolidated sediments." The DupiTila structure consists of unbending to fine sandstone with yellow and light brown silt clay bands under rock group of "semi-consolidated sediments." Tipam formation composed of sandstone, pebble bed, and conglomerates is under the rock category of "semi-consolidated sediments." The Bhuban and Boka Bil formations under the Surma group ("semi-consolidated sediments" rock type) are made of gray to brownish-gray massive shale sandstone-siltstone with limestone beds.

Geomorphologically, the territory of Tripura is juvenile and stands for the first-order terrain. The N-S organized hillsides are anticlinal and interceding basins are synclinal. Five hill ranges and valleys are present

in Tripura. The drainage arrangements are of dendritic and rectangular styles.

Materials and methods

Sampling and analytical methods

About 38 samples were stored in HDPE bottles (1-L capacity each) after 10 min of flushing out of each tube well water. Physical parameters including electrical conductivity (EC), dissolved oxygen (DO), turbidity, pH, and total dissolved solid (TDS)(Table 2) were analyzed in sampling locations immediately after collecting the sample. Samples were acidified with 7.9 N nitric acid solution (1:1) in each sample to make pH < 2. The chemical parameters (alkalinity, calcium (Ca), TH, magnesium (Mg), chloride (Cl$^-$), and Fe) (Table 2) were tested in the laboratory using standard protocol, American Public Health Association (APHA)(2012). pH was tested using a THOSCON pH meter of TMP 3 model. Turbidity measurement was done by turbidity meter (Labtronics, Model LT-33). DO value was measured with a digital DO meter (Labtronics, Model LT-18). EC and TDS values were checked by EI (Electronics India) equipment. Before conducting experiments, all instruments were pre-calibrated using standard operating procedures. The alkalinity analysis was performed by an acid titration method utilizing phenolphthalein and mixed indicator (bromocresol green and methyl red). Mg, Ca, and TH were analyzed using an EDTA titration method. Cl$^-$ was determined using silver nitrate titration method (potassium chromate indicator). Fe concentration was measured by phenanthroline method using UV spectrophotometer (PerkinElmer Lambda 35) at 510 nm. All measurements were performed three times and an average value was taken for further interpretation. The spatial distribution map was prepared using the inverse distance weighted (IDW) interpolation technique (Natesan et al. 2021) in the ArcGIS v.10.7.1 software. IDW estimates cell values by averaging the values of sample data points in the neighborhood of each processing cell specifying a lower power that will give more influence to the points that are farther away, resulting in a smoother surface.

Calculation of WQI

WQI values of 38 samples were estimated taking 11 variables to obtain their fitness towards drinking. To calculate WQI, two methods (EWWQI and WAWQI) have been employed.

Table 2 Basic statistical summary of physicochemical parameters

Parameters (unit)	Minimum	Maximum	Mean	Median	SD	WHO permissible limit
pH (unitless)	5.05	6.67	5.88	6.04	0.492	6.5–8.5
EC (μmho/cm)	42.66	775	169.30	153	123	250
TDS (mg/L)	19.23	750.5	89.53	70.76	113.56	500–1000
DO (mg/L)	1.5	7.6	4.38	4.5	1.615	5
Turbidity (NTU)	0.047	148.1	16.146	4.10	28.55	5
Alkalinity (mg/L)	204	358	128.05	120	91.223	200
Ca (mg/L)	0	54.779	11.755	9.402	10.559	75–200
Mg (mg/L)	5.457	210.56	37.852	30.674	35.869	50
TH (mg/L)	7.921	265.346	49.609	37.624	45.986	500
Cl⁻ (mg/L)	1	127	31.88	20	33.727	350
Fe (mg/L)	0.898	15.238	4.681	2.613	4.031	0.3–1

SD standard deviation, *EC* electrical conductivity, *TDS* total dissolved solid, *DO* dissolved oxygen, *TH* total hardness

Calculation of EWWQI

The thought, information entropy was first created by Shannon (1948) to quantify the level of confusion and vulnerability of a framework. EWWQI is a widely accepted technique over other WQIs, as EWWQI method does not require any personnel judgments on assignments of weight to each parameter (Amiri et al. 2014). The formulation of EWWQI requires the following steps (Adimalla 2021):

- Development of a matrix taking analyzed values of parameters of each sample.
- Construction of normalization matrix considering normalized values of each analyzed parameter to eradicate errors caused by different units and dimensions.
- Estimation of information entropy based on these normalized values which is formulated by Shannon (1948):

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^{m} P_{ij} \ln P_{ij} \qquad (1)$$

where *m* represents the no. of sampling areas and P_{ij} is the possibility of occurrence of normalized value (y_{ij}) of *j*th evaluated parameter in *i*th sample which is given by the following equation:

$$P_{ij} = y_{ij} \Big/ \sum_{i=1}^{m} y_{ij} \qquad (2)$$

- Then, entropy weight can be resolved so that lower entropy parameters have been given more weightage.

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{n} 1 - e_j} \qquad (3)$$

- Finally, EWWQI can be formulated by accumulation of entropy weight and quality rating scale.

$$EWWQI = \sum_{j=1}^{n} w_j \times q_j \qquad (4)$$

where q_j is the ratio of analyzed value of *j*th parameter (C_j) to its World Health Organization (WHO)(2011) recommended standard value (S_j).

$$q_j = \frac{C_j}{S_j} \times 100 \qquad (5)$$

Several researchers (Adimalla 2021; Amiri et al. 2021; Fagbote et al. 2014) have applied this technique to determine WQI. Based on estimated WQIs, they utilized Table 3, where groundwater can be categorized into 5 different categories for drinking, from "excellent to extremely poor" (Amiri et al. 2021).

Calculation of WAWQI

WAWQI technique was primarily proposed by Horton (1965) and successively modified by Brown et al. (1970) and Cude (2001). Three steps are to be pursued to achieve WQI: The initial step is the computation of weightage unit of *j*th

Table 3   Classification of groundwater quality based on EWWQI value

EWWQI	Water quality	Sample code with iron	Sample code without iron
< 50	Excellent	GW3, GW4, GW5, GW7, GW10, GW12, GW14, GW 16, GW22, GW24, GW37, GW38	GW1, GW3, GW4, GW5, GW6, GW7, GW10, GW11, GW12, GW14, GW16, GW19, GW20, GW22, GW24, GW32, GW37, GW38
50–100	Good	GW1, GW6, GW11, GW15,GW19, GW20, GW25, GW28, GW32, GW36	GW2, GW9, GW15, GW21, GW23,GW25, GW27, GW28
100–150	Medium	GW9, GW21, GW23, GW27, GW29	GW13, GW29, GW34
150–200	Poor	GW2, GW13	GW18, GW26, GW31, GW35
> 200	Extremely poor	GW8, GW17, GW18, GW26, GW30, GW31, GW33, GW34, GW35	GW8, GW17, GW30, GW33

parameter and it is inversely related to S_j for that corresponding parameter. Therefore, the mathematical equation for the weightage unit is

$$w_j' = \frac{K}{S_j} \tag{6}$$

where K is the proportionality constant which can be determined as follows:

$$K = \frac{1}{\sum\limits_{j=1}^{n} \frac{1}{S_j}} \tag{7}$$

The second step is the formulation of quality rating (q_j) for jth parameter by using the same Eq. 5 as used in the EWWQI method. The last step is the computation of WQI by aggregation of quality rating with the unit weight which is given by following equation:

$$WAWQI = \frac{\sum\limits_{j=1}^{n} w_j' \times q_j}{\sum_{j=1}^{n} w_j'} \tag{8}$$

Several researchers (Khatri et al. 2020; Ram et al. 2021) used this technique to estimate WQI. Depending upon the estimated WQI, the status of water for human consumption can be categorized as per Table 4 (Khatri et al. 2020).

Multivariate statistical analysis

Correlation coefficient (r) is calculated statistically and its value may be positive or negative and may be ranged from − 1 to + 1. r values of + 1 and − 1 indicate strong and inverse linear relationships, respectively, between variables.

PCA is a tool to decide an autonomous variable by taking out exceptionally related parameters. It evaluates the variance of interconnected variables by taking complex datasets and transformed them into less number of pseudo-variables. The steps for PCA are as follows (Nath et al. 2021):

- Correlation coefficient matrix calculation: the datasets are appropriate to do PCA if r values between parameters are appeared to be high
- Identifying the number of factors to be kept relying upon % of variance and eigenvalues

Table 4   Category of groundwater quality according to WAWQI value

WAWQI	Water quality	Sample code with iron	Sample code without iron
0–25	Excellent	–	–
26–50	Good	–	–
51–75	Poor	–	GW3, GW4, GW6, GW7, GW12, GW14, GW15, GW16, GW19, GW20, GW22, GW24, GW37, GW38
76–100	Very poor	GW3, GW4, GW14, GW15, GW16	GW1, GW5, GW10, GW11, GW25, GW27, GW28, GW32, GW36
> 100	Unsuitable for drinking	GW1, GW2, GW5, GW6, GW7, GW8, GW9, GW10, GW11, GW12, GW13, GW17, GW18, GW19, GW20, GW21, GW22, GW23, GW24, GW25, GW26, GW27, GW28, GW29, GW30, GW31, GW32, GW33, GW34, GW35, GW36, GW37, GW38	GW2, GW8, GW9, GW13, GW17, GW18, GW21, GW23, GW26, GW29, GW30, GW31, GW33, GW34, GW35

- Factors rotation to enhance their clarification by maximizing loading of parameters

Kaiser–Meyer–Olkin (KMO) and Bartlett's sphericity tests have been executed to confirm whether PCA is reasonable or not for the present experimental dataset. KMO index measures the satisfactoriness of samples. The entire analyzed datasets will not be appropriate for PCA if this index shows a < 0.5 value. In the present study, PCA is applicable as this value is 0.722. Bartlett's sphericity test has been performed to acquire correlation matrix's nature whether this is a uniqueness matrix or not. Null hypothesis is not considered for PCA through Bartlett's sphericity test because this hypothesis already considers the uniqueness of correlation matrix. In the present investigation, the significance level (0.00) is < 0.05 which discard null hypothesis and it affirms the presence of a strong relationship among parameters. Finally, PCA technique has been implemented on normalized dataset using varimax rotation (to maximize factor loadings) and Kaiser's principle (Kaiser 1960) to achieve principal factors.

CA was interpreted to group monitoring sites and to determine whether each sample had similar physicochemical (inherent) characteristics. In CA, every sample forms an individual cluster and a pair of clusters is combined depending on similarity (measured by squared Euclidean distance) and applied linkage technique (Ward's method). This method utilizes an ANOVA technique to determine differences between each cluster. The outcomes are demonstrated by a dendrogram plot, providing a basic image of the cluster (groups)(McKenna 2003). IBM Statistical Package of Social Studies (SPSS) version 21 was employed to make PCA and CA assessments.

Results and discussion

Table 2 represents the basic descriptive statistics of environmental parameters of groundwater samples. The mean value of all parameters was within WHO contaminant level for drinking except few cases suggesting local contamination sources.

Physicochemical parameter analysis

pH represents the presence of H^+ ion and acidity or basic nature in water. In water body, all types of reactions (chemical, biological, physical, etc.) depend on pH (Rao 2006). The average value of pH was 5.88 ± 0.492 (Table 2) which was below WHO contaminant level (World Health Organization (WHO)2011). However, 79% of samples showed acidic nature because of

dissolved CO_2 and discharge of effluents from industrial waste. pH confirmed strong correlation with alkalinity (r = 0.751) (Table 6) as higher pH raises alkalinity level resulting in the conversion of all dissolved CO_2 to CO_3^- and HCO_3^- ions.

EC refers to a substance ability to conduct electrical current through water. The mean EC was 169.30 μmho/cm(Table 2), while only 13% of samples exceeded WHO standard limit of 250 μmho/cm. The highest EC can damage crop yield and soil structure as water transparency is directly proportional to crop yield. Geochemical processes including reverse and direct ion exchange, high evaporation, silicate weathering, and rock-water association are various causes of high EC values (Alfaifi et al. 2020). EC showed strong correlation with Ca (r = 0.909), Mg (r = 0.948), and TH (r = 0.949) and moderate correlation with Cl^- (r = 0.632) (Table 6)(Panghal and Bhateria 2020), suggesting all ions (cations and anions) have a common source and geochemical process. Figure 2f depicts the highest EC value in the central part of Agartala City, located in the western part of the study area. Northern and southern parts have observed low to very low (< 114.50 μmho/cm) EC.

TDS represents inorganic salts of Mg, Ca, Na, K, and Cl^- dissolved in groundwater (Adimalla et al. 2018). In this study, TDS ranged from 19.23 to 750.5 mg/L with an average value of 89.53 mg/L showing all samples within WHO limit of 1000 mg/L (World Health Organization (WHO)2011). A higher level of TDS prompts drinking water to be of bitter taste, brackish, and salty which in turn can harm aquatic species present in water. Higher dissolved salts pointing to high EC show perfect correlation with TDS (r = 0.946) (Table 6).

DO is an essential organic parameter to assess the fitness of water for keeping up human well-being and oceanic life. The average DO of groundwater was 4.38 ± 1.61 (Table 2). About 37% of samples were much below WHO prescribed limit (World Health Organization (WHO) 2011) contributing to decomposition and die-off of submerged plants. Turbidity (high concentration) absorbs sunlight and produces warm water, thereby reducing DO level, confirming weak negative relationship with turbidity (r = − 0.315). The maximum concentration of DO has been reported in the northwestern to the western portions of the study area. Some pockets of the southern part also have high concentration of DO. However, northeastern and southeastern parts of the district observed poor concentration of DO (Fig. 2c).

Turbidity is an indication of optical quality that reflects the suspended particles present in water via dispersion of light (Kumar and Krishna 2021). The analyzed mean turbidity was 16.14 NTU with 45% samples exceeded WHO standard limit of 5 NTU. Only one monitoring station (GW17) showed a turbidity value
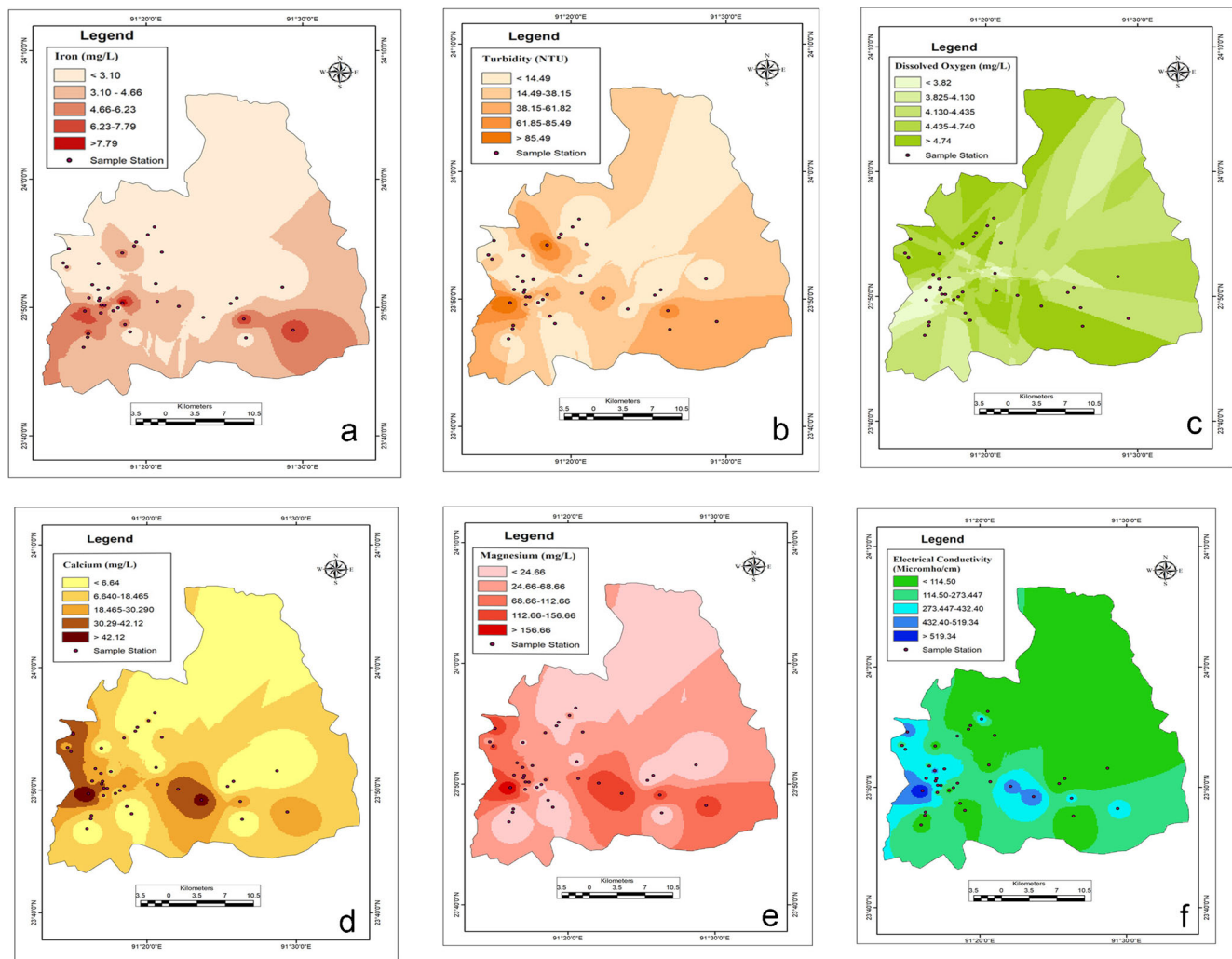
Fig. 2 Spatial distribution maps of physicochemical parameters showing concentrations of **a** iron (Fe), **b** turbidity, **c** dissolved oxygen (DO), **d** calcium (Ca), **e** magnesium (Mg), and **f** electrical conductivity (EC)

(148.1) about 30 times higher than the WHO limit. With the rising of water levels due to rapid and copious raining, suspended and dissolved solids in water also raises which in turn increases turbidity. Turbidity derives from insoluble Fe particles (colloidal form) and excessive dissolved metal produces turbid water, showing moderate correlation with Fe ($r = 0.636$) (Table 6). From Fig. 2b, the western and southeastern parts have the highest turbidity than northeast of the central part.

Alkalinity represents the presence of carbonate, bicarbonate, and hydroxide compounds of sodium, potassium, and Ca in water. Alkalinity varied from 204 to 358 mg/L(Table 2) with an average of 128.05 mg/L showing 26% of samples were alkaline in nature. Too much alkalinity can change the normal pH of body prompting numerous human health issues like nausea, vomiting, and bone problems. Excessive alkalinity leads

to the formation of corrosive effect in boiler known as "embrittlement."

Mg and Ca are essential elements for biological growth. The source of Mg and Ca in groundwater mainly emerges from calcite, dolomite, and magnetite rock. Excessive concentrations of Ca lead to stone formation in human body adversely destroying human health. Again lack of Ca can cause rickets in human bodies. In the present study, the average value of Ca and Mg was 11.75 mg/L and 37.85 mg/L(Table 2), while Mg in 21% samples overstepped the WHO standard limit of 50 mg/L. The western part near Agartala City and southeastern fringe reported maximum Mg concentration than the northern part (< 24.66 mg/L) of the study area (Fig. 2e). From Fig. 2d, the western edge and south-central part observed maximum Ca than the northern part. A gradual decrease of Ca in groundwater has been taken place from the northwestern to southern portions of the district.

TH is obtained from the summation of Mg and Ca hardness. All samples categorized as soft water with hardness values of 7.921–265.346 mg/L with an average value of 49.609 mg/L were reported. Soft water can increase heavy metal (copper, zinc, lead, etc.) solubility in water. This also increases scale deposition in pipes (pipe corrosion) which prevents heat transfer through the pipe causing a serious environmental problem. TH exceeding 150–300mg/L can spoil the kidney by developing stone in the kidney and it reduces soap's ability to produce lather. Mg confirmed more good correlation with TH ($r = 0.99$) (Table 6) than Ca ($r = 0.96$) does. This statement confirmed that TH was primarily dominated by Mg. The correlation of TH, Ca, and Mg specifies contamination due to minerals or geologic sources.

Cl$^-$ in groundwater at higher dose can cause laxative effects. In the present investigated area, the mean Cl$^-$ concentration was 31.88 mg/L(Table 2) showing all samples within WHO contaminant level. Cl$^-$ ion above 350 mg/L increases EC which causes metal corrosivity, thus increasing metal levels in potable water. Excess Cl$^-$ ion is an indication of contamination from various sources and it also creates salty water (Marghade et al. 2012).

Fe exists in groundwater either in + (II) or + (III) oxidation state depending on anaerobic or aerobic conditions. The average Fe value was 4.68 ± 4.03 mg/L(Table 2) with 89% of

samples exceeded WHO prescribed limit of 0.3–1 mg/L. This demonstrates that the monitored location is exceptionally influenced by Fe contamination. The higher Fe value might be credited to the leaching of Fe-bearing minerals into groundwater and low groundwater level. Excessive Fe concentration transforms water color to reddish-brownish and is capable to enhance bacterial growth (Awomeso et al. 2020). The intake of too much Fe has been shown to harm the blood vessels, liver, pancreas, and kidneys and can sometimes results in death. Bloody stool and vomiting are common side effects of excessive Fe consumption (Panghal and Bhateria 2020). Overexposure to Fe has been linked to diabetes, fatigue, abdominal pain, and in some cases impotence among other health consequences. The southeastern and southwestern parts of the study area reported more Fe contamination comparing to the northern and central parts (Fig. 2a). It has also been observed that especially southern bank of river Haora has more Fe contamination than the northern part. Other studies reported Fe concentration as 0.01–19.28 (Singh and Kumar 2015), 0.22–5.07 (Paul et al. 2019a), 0.12–5.14 (Paul et al. 2019b), and 0.05–5.39 (Brindha et al. 2020) mg/L.

The Fe concentration is varying in different sub-surface layers. The average value of Fe content is high in near to land surface and relatively poor concentrations have been found in higher depth of land surface. About 18% samples have high
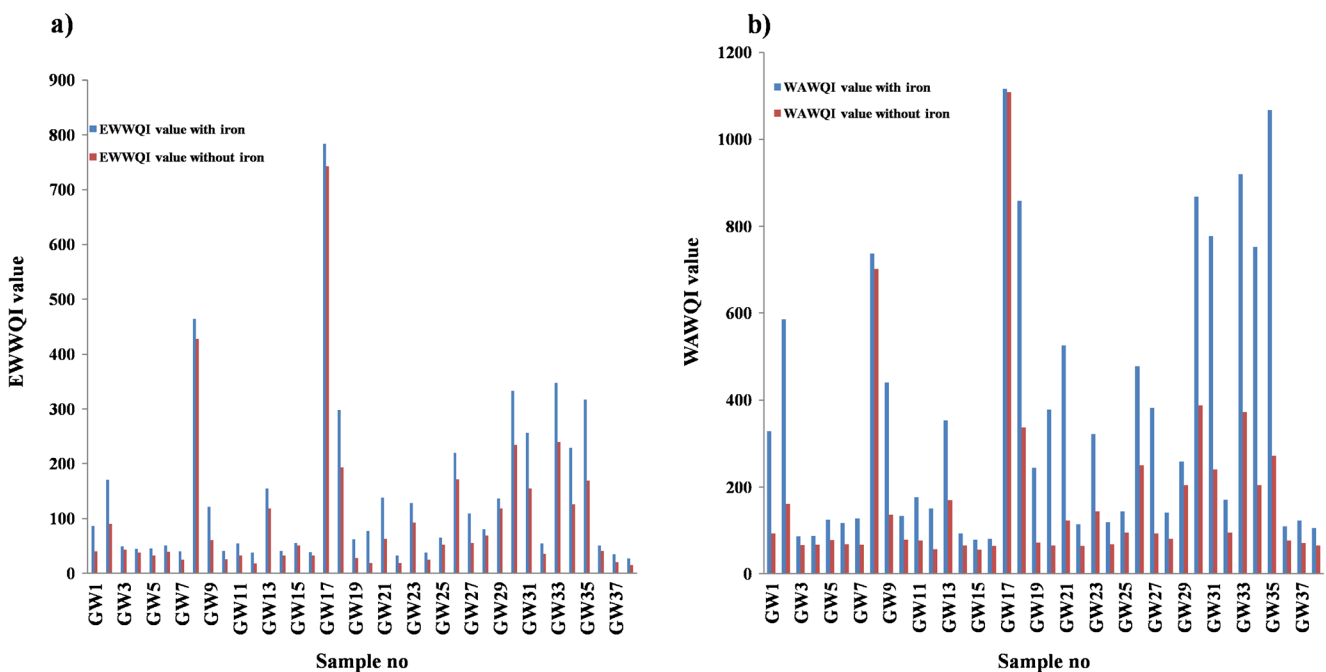

Fig. 3 WQI values according to **a** entropy weight method and **b** arithmetic weight method

Fe contamination (> 7.79 mg/L). Maximum sample stations of this group are located in the western part of the research area where groundwater has been collected mostly from < 20 m bottom of the earth surface specially Kalyani, Women's College, Bodhjungnagar area. About 53% of sample stations have been found from 20 to 40 m depth of the surface. It is also found that Fe contamination is significantly lower in these areas. The rest of 29% of sampling station reflects that groundwater has been collected from more than 40 m depth from the earth's surface. The study reveals that Fatikchara, Shantipur, Salbagan, Narsinghgarh Bazar, and Hapania areas have a relatively very low level of Fe. It signifies that, with an increase of depth of the soil layer, geochemical properties of groundwater are reduced proportionately. Geological and morphological structures of the region have strong relation among the depth of the earth surface and ground water quality (Fig. 2a).

WQI analysis

WQI is estimated utilizing two strategies in the present reported area. To know the gravity of concern regarding Fe contamination, EWWQI and WAWQI values are also estimated considering 10 parameters where iron concentration is not included. The research additionally features percent decrease of two WQI considering with and without Fe as per following equation

%decrease of WQI

$$= \frac{\text{WQI with iron} - \text{WQI without iron}}{\text{WQI with iron}} \times 100 \qquad (9)$$

From estimated results of EWWQI as reflected in Fig. 3a and Table 5, almost 58% of samples are of "excellent" to "good" category, five samples are of "medium" category, and 29% samples are under "poor" to "extremely poor" category. Out of 29% poor category samples, 18% sample belongs to extremely populated capital city, Agartala. Depending on EWWQI values (Table 5; Fig. 3a) excluding iron concentration, 71% of samples cover "excellent" to "good" category, three samples are of "medium" standard, and "poor" to "extremely poor" category are shown by 21% samples. According to Eq. 9, percentage decrease of EWWQI between 50–80, 40–50, 30–40, 20–30, and 0–20 are detected in five, nine, seven, seven, and ten groundwater samples, respectively. Figure 4 depicts spatial distribution of EWWQI with and without Fe. From Fig. 4a, groundwater quality in the southern and northeastern

parts is very poor. Although, it has been depicted that about 10 areas especially the western and central parts

Table 5 EWWQI and WAWQI values of groundwater samples

| Sample no.	EWWQI value		WAWQI value	
	With iron	Without iron	With iron	Without iron
GW1	86.50	40.34	328.41	92.97
GW2	171.28	90.69	585.79	161.27
GW3	49.09	43.17	86.21	66.53
GW4	44.92	38.24	87.81	67.43
GW5	45.68	32.73	124.50	77.62
GW6	51.10	39.63	116.88	68.21
GW7	40.30	25.40	127.40	67.26
GW8	463.83	427.89	737.13	702.11
GW9	121.48	61.07	440.26	136.21
GW10	40.83	25.67	133.18	78.40
GW11	54.60	32.62	176.80	76.86
GW12	38.41	18.02	150.95	57.04
GW13	155.52	118.42	353.20	169.56
GW14	41.12	32.75	93.33	65.15
GW15	55.76	51.31	78.78	55.38
GW16	38.88	32.65	80.47	64.22
GW17	783.93	742.78	1116.01	1109.27
GW18	298.51	193.33	858.32	337.26
GW19	62.65	28.33	244.20	72.24
GW20	77.47	18.71	378.00	65.64
GW21	138.80	63.05	526.07	123.13
GW22	32.71	19.22	114.02	63.84
GW23	128.79	92.66	321.67	143.58
GW24	38.19	24.78	118.67	68.24
GW25	65.31	52.32	143.56	95.02
GW26	219.60	171.85	478.20	249.23
GW27	109.29	55.60	381.99	93.17
GW28	80.81	69.15	141.17	80.27
GW29	137.06	118.52	257.93	204.67
GW30	333.48	234.34	867.58	387.62
GW31	256.61	155.05	777.46	239.88
GW32	54.94	35.43	170.68	94.80
GW33	347.93	239.48	919.54	372.34
GW34	228.80	126.15	752.44	204.35
GW35	317.48	169.70	1067.65	272.07
GW36	50.86	41.36	109.62	76.71
GW37	34.78	20.43	122.48	71.19
GW38	27.50	15.13	105.34	64.97
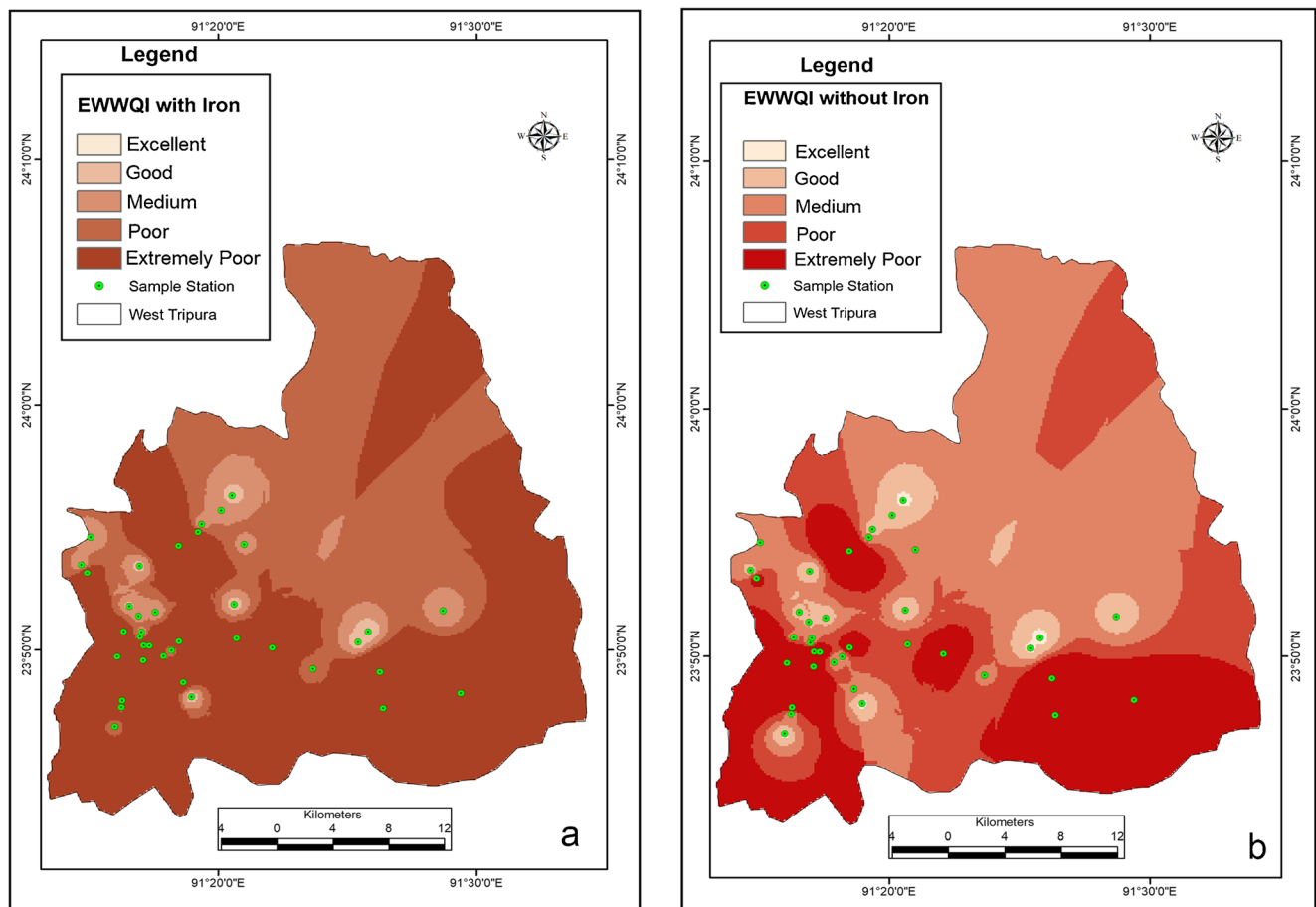
Fig. 4 Spatial distribution maps of EWWQI **a** with iron and **b** without iron

have good to excellent quality of groundwater. But from Fig. 4b, EWWQI without Fe portrays extremely poor water quality in the southwestern and southeastern parts, while about six micro-regions are found in the central and western parts of the study area, where groundwater quality is excellent. As per EWWQI without Fe, overall, good quality groundwater is observed in the central part of the area.

From WAWQI values (Fig. 3b; Table 5), only five samples cover "very poor" standard and the remaining all other samples are "unsuitable" for drinking, whereas without considering Fe concentrations, 60% (23) of samples are of "poor" to "very poor" category and the remaining samples fall under "unsuitable" category. Percent decreases of WAWQI values estimated as per Eq. 9 were noted as 70–90, 50–70, 40–50, 30–40, and 0–30 for eight, nine, nine, five, and seven samples

respectively. Figure 5 depicts the spatial distribution of WAWQI with and without Fe. According to Fig. 5a, groundwater quality of the entire study area is unsuitable for drinking. On the other hand, Fig. 5b depicts that the entire study area has very poor groundwater quality except 14 small pockets located in the central and western parts of the study area.

GW17 shows the highest WQI value in both methods as EC, Mg, TDS, Fe, and turbidity concentration in this sample exceeded the WHO permissible limit. Again, from the r value, a strong positive relationship exists between EC, Mg, turbidity, and TDS. Also, Fe and turbidity show a strong relationship. Geological strata and underlying groundwater containing excessive minerals led to increased levels of ions (EC, Mg) and TDS. High concentrations of ions suggest processes of leaching and rock-water interaction deteriorating water
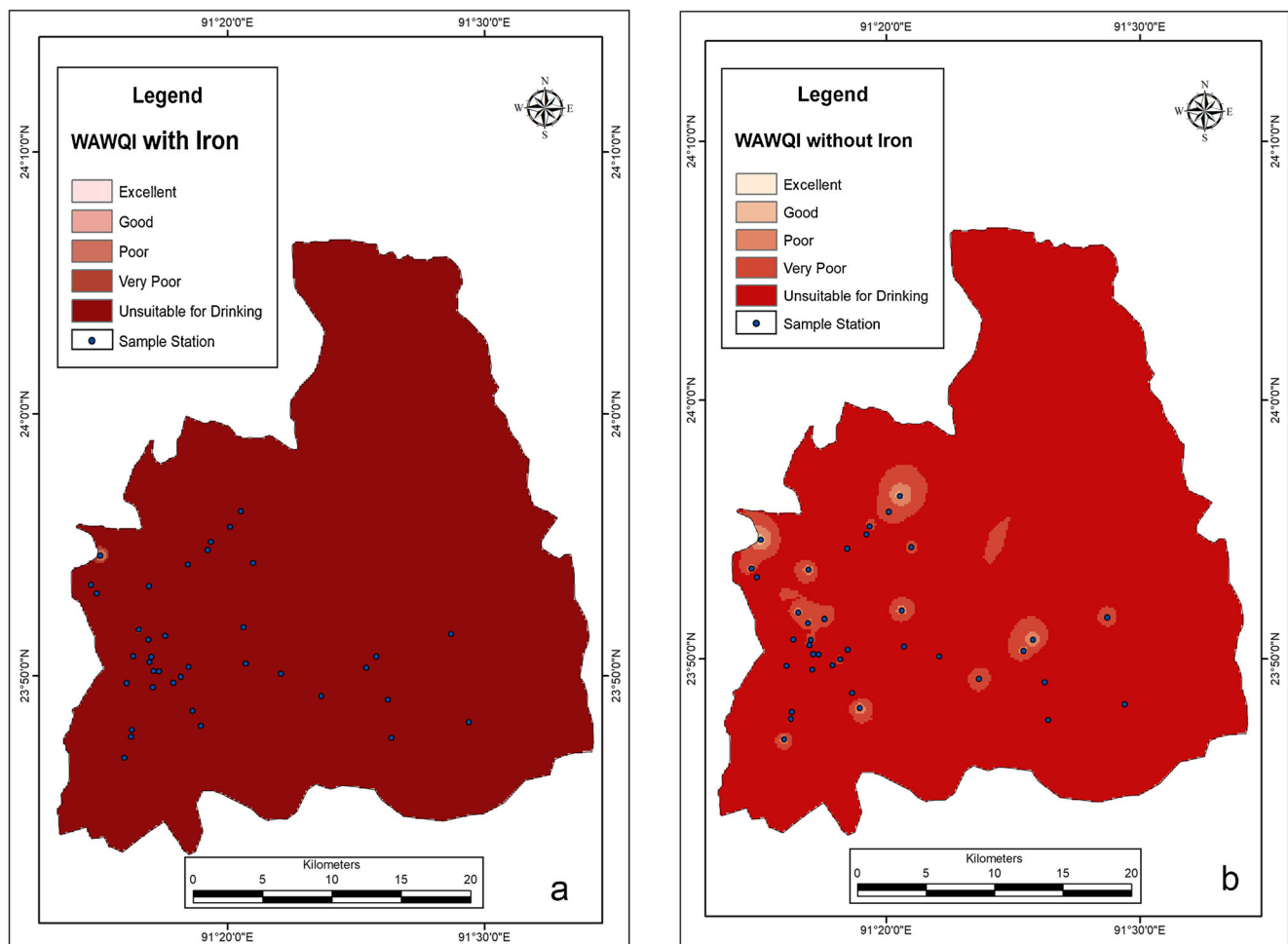
Fig. 5 Spatial distribution maps of WAWQI **a** with iron and **b** without iron

quality. Excessive Fe and turbidity concentration may be due to improper waste disposal, inappropriate maintenance, and functioning of a septic system. Excessive utilization of groundwater enhances Fe concentration in this location. Moreover, GW17 (Battala) is located in Agartala City where WQI value is much higher than other samples because thick population and anthropogenic sources degrade groundwater quality.

Principal component analysis

PCA technique is applied to recognize individual loadings of 11 variables in water quality. Generally, eigenvalues are utilized to achieve principal components (PCs). An eigenvalue determines major variables with maximum value. Eigenvalues ≥ 1 are considered as the most significant (Muangthong and

Shrestha 2015). PCs with eigenvalues < 1 were discarded on account of their low essentialness.

A scree plot diagram (Fig. 6a) has been established where the first three factors show their eigenvalues > 1. This figure shows a minor fall in slope after the third eigenvalue. Therefore, only the first three components with a total variance of 84.5% have been decided. The percentage variance, eigenvalues, and loadings of 3 PCs are given in Table 7. The PC loadings were sorted as strong (> 0.75), moderate (0.75–0.50), and weak (0.50–0.30) (Liu et al. 2003).

The first component (PC1) accounting the largest proportion in total variance (56%) (Table 7) had positive loadings for EC, TDS, Mg, TH, Ca, and Cl⁻. This may be credited to the source of natural water (Simeonov et al. 2001) and this factor is termed as "water hardness salinity" factor. However, strong
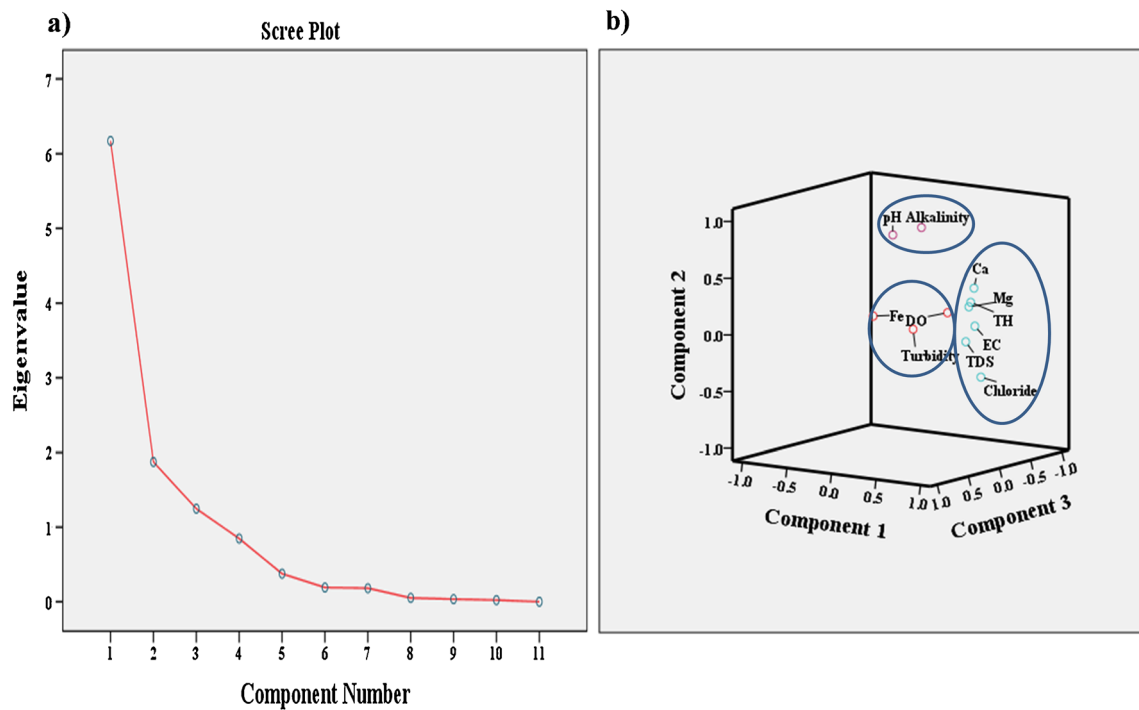
a)

b)

Fig. 6 Principal component analysis by **a** scree plot and **b** 3D loading plot

loading of Ca, TH, and Mg in PC1 specifies the origin of groundwater from rock-water association with weathering process of dolomite and calcite. In PC1, dissolved salts of Ca, Cl⁻, and Mg have the greatest

influence on water quality (Kumar and Krishna 2021). PC2 clarifies about 17% (Table 7) of the total variance, where pH and alkalinity had a strong influence. This strong relationship is likewise found from r value (r =

Table 6 Correlation coefficient (r) matrix of groundwater samples

Parameter	pH	EC	TDS	DO	turbidity	alkalinity	Ca	Mg	TH	Cl⁻	Fe
pH	1.000										
EC	0.261	1.000									
TDS	0.187	**0.946**	1.000								
DO	− 0.233	− 0.144	− 0.199	1.000							
Turbidity	0.373	0.688	**0.764**	− 0.315	1.000						
Alkalinity	**0.751**	0.306	0.179	0.004	0.224	1.000					
Ca	0.511	**0.909**	**0.825**	− 0.056	0.591	0.549	1.000				
Mg	0.425	**0.948**	**0.913**	− 0.134	**0.724**	0.430	**0.946**	1.000			
TH	0.449	**0.949**	**0.901**	− 0.118	**0.701**	0.461	**0.967**	**0.997**	1.000		
Cl⁻	− 0.254	0.632	0.582	0.066	0.250	− 0.123	0.454	0.494	0.489	1.000	
Fe	0.353	0.300	0.300	− 0.148	0.636	0.194	0.250	0.339	0.322	− 0.022	1.000

Bold values indicate strong relationships

Table 7 Loading values of principal component of groundwater samples

Parameters	PC1	PC2	PC3
pH	0.115	**0.887**	0.291
EC	**0.956**	0.151	0.176
TDS	**0.927**	0.026	0.280
DO	0.011	0.043	**− 0.735**
turbidity	0.606	0.159	**0.667**
alkalinity	0.202	**0.913**	− 0.044
Ca	**0.862**	0.461	0.055
Mg	**0.908**	0.322	0.203
TH	**0.906**	0.357	0.171
Cl⁻	**0.776**	− 0.368	− 0.179
Fe	0.177	0.237	**0.695**
Eigenvalue	6.172	1.875	1.248
% of variance	56.111	17.049	11.348
Cumulative %	56.111	73.159	84.507

Extraction method: principal component analysis. Rotation method: varimax with Kaiser normalization. Rotation converged in 5 iterations. Bold values indicate strong and moderate loadings

0.751) (Table 6). PC2 represented here the physical aspects of water by which water acidic or basic nature can be communicated. PC3, contributing just 11% (Table 7) of the total variance, had moderate positive coefficients (Fe and turbidity) but was negatively loaded with DO. This statement is in agreement with the acquired results of r (Table 6). This factor (PC3) may be credited to the dissolution of solids making turbid water and pollution because of harmful toxic metal contamination.

Figure 6b shows a 3D plot of PCA loading values. This figure affirms that a solid association exists among pH and alkalinity (represents acidic or basic water source). Fe, DO, and turbidity in one group signify some metallic ions suspended in water and make water turbid. Again EC, TDS, Mg, TH, Ca, and Cl⁻ are derived from a single group (corresponds to water hardness and dissolution of solids).

Cluster analysis

CA derives three clusters out of 38 monitoring sites. Cluster 1 includes 20 stations, divided into two subgroups (22, 24, 37, 20, 32, 7, 21, 9, 38, 10, 12, 1, 25, 19, 14, and 18) and (5, 6, 11, 30) (Fig. 7). This

cluster is termed as a less polluted zone as 18 samples except two (GW18 and GW30) that have good water quality. Cluster 3 comprises of only one sampling station (GW17), termed as a highly contaminated region as in the "WQI analysis" section where it has been already discussed that GW17 has the highest WQI value due to the thickly populated region and anthropogenic activities. Cluster 2 covers the remaining 17 sites (Fig. 7) considered as moderately contaminated regions, having 8 samples of poor quality water. Comparing to cluster 1, cluster 2 has more number of poor quality water samples, that is why it is considered a moderately polluted region. Linkage distance of cluster 1 and cluster 2 are less than cluster 3 indicating that samples in cluster 1 and cluster 2 have almost similar characteristics to cluster 3.

Another dendrogram view of parameter cluster analysis is shown in Fig. 8. Here, cluster 1 includes five environmental parameters: pH, DO, Fe, Ca, and turbidity. This cluster may be from the natural and metallic sources along with the rock-water interaction process. Cluster 2 covers three parameters: TH, Mg, and Cl⁻, indicating hardness source is mainly dominated by Mg and the dissolution of Cl⁻ in groundwater. High Mg content than Ca suggests weathering of minerals like dolomite and magnesite. Cluster 3 comprises of EC, TDS, and alkalinity, which could be attributed to ionic influence and salt concentration in groundwater.

Conclusions

To obtain the present status of fitness of groundwater for drinking, a few investigation techniques like WQI, correlation analysis, CA, and PCA have been employed effectively based on analyzed data of 38 groundwater samples. According to the outcomes of WQI, the higher values of Fe and turbidity play a significant commitment to make non-potability of groundwater. Comparing two WQI methods, the EWWQI method gives more precise and reliable outcomes than the WAWQI method because the EWWQI method consistently avoids personnel judgments (that assume weightage factor to each water quality parameter), which are mulled over for the WAWQI method. The WAWQI technique does not provide detailed information about the actual condition of groundwater due to over-emphasizing phenomena. In this study, 11 parameters are reduced into 3 underlying factors (PC1, PC2,

Fig. 7 Cluster analysis of sampling locations
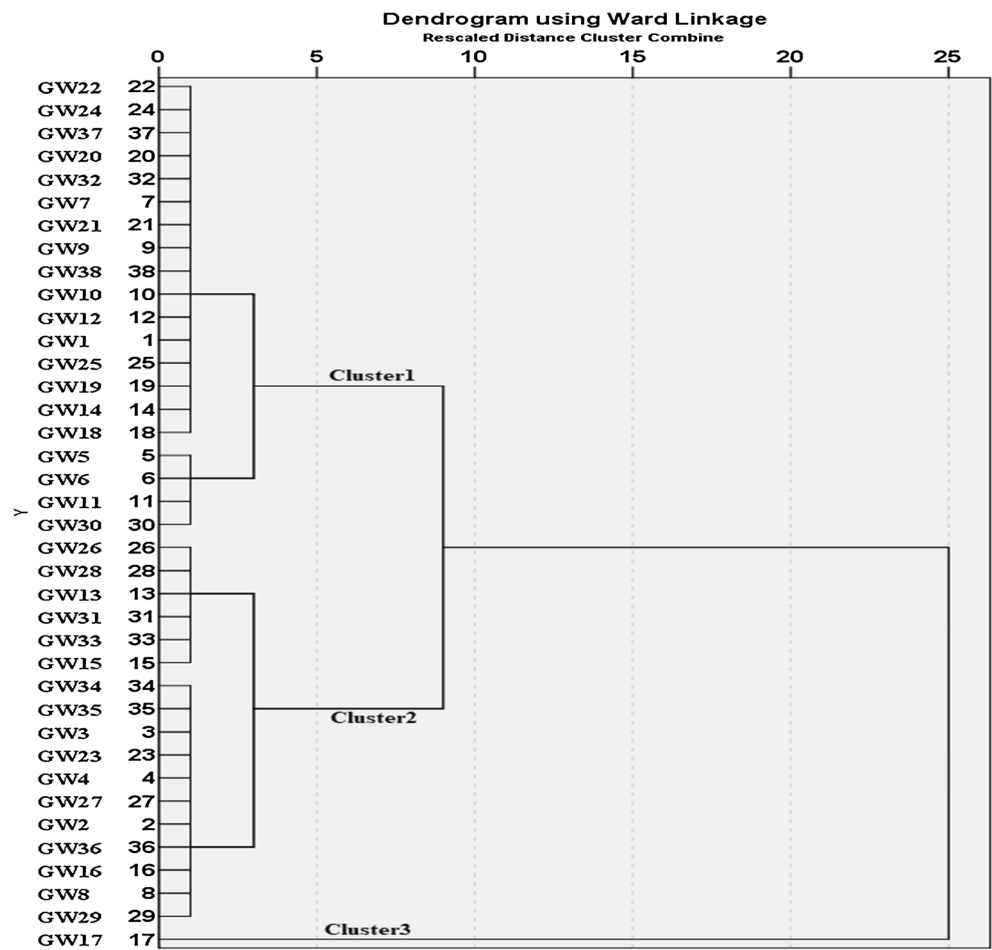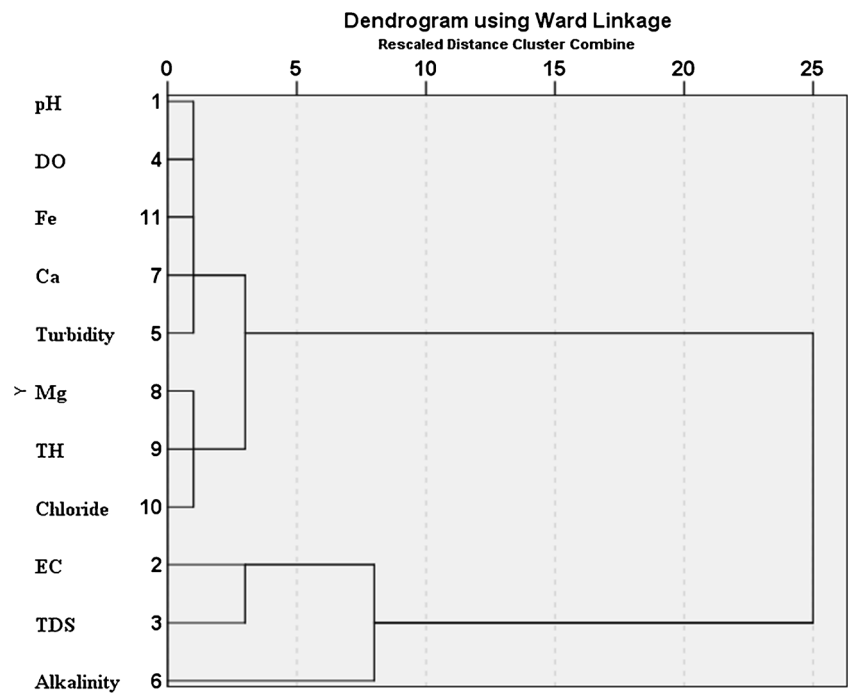

Fig. 8 Cluster analysis of physicochemical parameters

and PC3) by the PCA method to distinguish water quality degradation. This technique reflects water quality deterioration because of the contribution of metallic ion concentration, turbidity, and DO for PC3; pH and alkalinity for PC2; and the remaining parameters responsible for PC1. CA results agreeably validate the outcomes of WQI. In this manner, from the above investigation, groundwater quality is ought to be observed routinely, and accordingly, treatment has to be adopted only when the sample will be not fit for drinking.

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