



Comparative assessment of groundwater quality indices of Kannur District, Kerala, India using multivariate statistical approaches and GIS

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Abstract The aim of the study was to determine the groundwater characteristics of rural and industrial zones in the Kannur region. In 2011, 25 groundwater data were collected from the centre for water resource development management (CWRDM), and in 2019, 25 groundwater samples from rural and near-industrial areas were collected and analysed for major anions (HCO_3^- , CO_3^{2-} , Cl^- , NO_3^- and SO_4^{2-}), and cations (TH , Ca^{2+} , Mg^{2+} , Na^+ , K^+ and Fe^{2+}) using APHA standards. To better understand the link between water quality parameters, multivariate statistical analysis approaches such as principal component analysis (PCA), hierarchical cluster analysis (HCA),

correlation matrix analysis (CMA), and Pearson correlation bivariate one-tailed analysis (PCBOTA) were used to analyse the inter-relationship of data. The Inverse Distance Weighed (IDW) method was used to generate the spatial distribution of the groundwater quality index (GWQI). In 2011, the water quality index (WQI) value of groundwater samples was excellent at 24.42% and good at 54.14%, which were used for drinking purposes and moderate at 17.22% and poor at 4.22% for irrigation purposes in this study area. In 2019, excellent 21.62%, good 51.56% were used for drinking purpose, and moderate at 18.14%, and poor at 8.68% for irrigation purposes. By comparing the data with BIS and WHO standards, it is clear that groundwater in Kannur district is of good quality. In groundwater samples, the PCA eigen values were reported in 2011 (84.7%) and 2019 (73.4%) for statistical approaches. This study uses HCA and PCBOTA to analyse the elements, resulting in a better understanding of groundwater quality development. GIS based WQI maps were obtained and utilised to gain a better knowledge of the study area's past and present water quality status. We observed that the quality of groundwater in the study region's north-western portion is insufficient for drinking water.

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Introduction

Groundwater is the most valuable resource in the world and it is used for household, horticultural, agricultural, hydropower generating, and other purposes by around 33% of the world's population (Macdonald et al., 2016; Nawab et al., 2016; Zhang et al., 2017; Su et al., 2020; Wang et al., 2020; Karunanidhi et al., 2021). Groundwater pollution has grown into an important element influencing the quality of all freshwater aquifer systems (Chandrasekar et al., 2021). The monitoring of a wide range of physicochemical properties, including cations and anions, is required for groundwater quality (Tiwari et al., 2018). Groundwater is an important natural resource for meeting our country's water needs (Gajbhiye et al., 2015). Groundwater wells are an important source of water for many people in Kerala's southwest region, and they serve as a source of water (Sapna et al., 2020a; Sefie et al., 2018). The quality of a region's groundwater varies from area to area. Many industrial effluents and contaminants are discharged into the environment untreated, allowing groundwater supplies to deteriorate (Thangavelu et al., 2019). Human health, animal welfare, and agriculture are all affected by this unethical groundwater (Arumugam & Elangovan, 2009). Groundwater can be contaminated by precipitation and surface discharge from polluted soil (Khodapanah et al., 2009).

Groundwater quality assessment involves more than evaluating its acceptability; it also includes demanding groundwater management in a more acceptable framework to meet current and future drinking and water system needs (Islam et al., 2015). The evaluation of groundwater quality includes far more than finding its acceptability; it is also about require groundwater management in a more acceptable framework to satisfy current and future needs for drinking and water system usage (Islam et al., 2015; Shanmugamoorthy et al., 2022). Water quality evaluations are carried out on a regional and international level by a many experts from various locations (Abbulu & Rao, 2013; Magesh et al., 2021a, b; Sajil Kumar et al., 2013; Sapna et al., 2018; Thangavelu, 2013). The analysts attempted to increase the number of water quality index (WQI) that monitor groundwater quality (Chaurasia et al., 2018; Nagaraju et al., 2016; Pandian & Jayachandran, 2014; Sapna et al., 2020b; Singh & Khan, 2011).

A Geographical information system (GIS) is an emerging tool to demonstrate the accuracy of water quality

mapping. In the past, a few researchers have analysed the issue of ground water quality by using GIS in different conditions (Emenike et al., 2018; Thangavelu et al., 2021). It was suggested by Balakrishnan et al. (2011) that the utilisation of GIS strategies is important in the assessment of groundwater pollution risk assessment methods and also groundwater quality planning. Reza and Singh (2010) used the water quality file approach to assess the state of groundwater quality. Emenike et al. (2018) investigated the geographical and hydrochemical links between groundwater quality.

A comparable technique was used for the evaluation of groundwater quality for drinking and water system usage in shallow hard rock springs in Kerala (Satish Kumar et al., 2016). It is difficult due to the spatial variation of the several contaminants that can be analysed. Arulbalaji and Gurugnanam (2017) have drawn more rapidly on groundwater quality evaluation in Tamilnadu, India, using geospatial and measurable devices. It was clearly focused on a physico-chemical evaluation of groundwater quality and its appropriateness for human and agricultural use. Several experts have investigated to develop the different groundwater quality index (GWQI) for groundwater analysis. It may be assessed using a number of factual approaches and models (Molla et al., 2015).

This analysis uses multivariate statistical methodologies to find new components that impact water systems. The combined measuring methodology and spatial interpolation techniques can help water systems. The water management sources elucidate better solutions for pollution issues within different parts of India and throughout the world (Halim et al., 2010; Rahman et al., 2012; Abinandan et al., 2014; Jeihouni et al., 2014). Statistical processes can be utilised in a simple and easy format to establish a numerical connection for physico-chemical studies (Iyer et al., 2003). It was decided to approach the statistical processes such as principal component analysis (PCA) and hierarchical cluster analysis (HCA) understand the meaning of this complex data set. The analysis of a coefficient correlation matrix and the Pearson relationship bivariate one tailed approach is a significant tool that will assist in the study of water pollution issues. Groundwater quality limits that result in large datasets needed for analysing difficult informational matrixes in order to have a better understanding of the water quality (Sapna et al., 2020b).

The investigation is focused on physical and chemical components that are inextricably related depending on

the physicochemical measurement and assessment locations. Many studies have been conducted on the physicochemical evaluation of groundwater quality in different locations. A few attempts have been made to assess groundwater quality using the correlation coefficient assessment of various water quality limits. Furthermore, a few methodologies were used to assess groundwater quality, which means it cannot directly indicate contaminated features (Bhasin et al., 2008).

The spatial distribution of groundwater quality method is used to identify areas where pollution poses a risk (Masoud, 2014). In addition, a few strategies were employed for the appraisal of groundwater quality, which cannot directly reflect contamination attributes (Adam et al., 2019). The spatial distribution of the groundwater quality index was created using spatial interpolation techniques such as the inverse distance weighted (IDW) approach (Islam et al., 2013; Thangavelu et al., 2019). IDW is approach that estimates groundwater sample values by averaging the values of sample data locations in the area of each processing and give an idea of the prediction accuracy and selection will be easy and appropriate. The objective is to understand and categorise groundwater quality in rural and industrial regions for spatial analysis using various physicochemical parameters. The study was compared physicochemical characteristics, multivariate statistics, WQI, and GIS to evaluate groundwater quality in the Kannur district.

Materials and methods

The study area's description

The Kannur region is surrounded by the Malabar territory of Kerala. The northern part of the zone is covered by Kasaragod district, the southern part of the territory is limited by the Kozhikode region, and the south-east part of the region is covered by Wayanad district. The Western Ghats, which form the boundary between the Karnataka state region of Kodagu and the Lakshadweep Sea toward the western part of the Arabian Sea. The total area covered is 2966 sq. km. It lies between $11^{\circ} 40' 00''$ and $12^{\circ} 20' 27''$ northern latitude and $75^{\circ} 10' 00''$ and $75^{\circ} 56' 30''$ eastern longitude. High lands, midlands, and lowlands are the three geological districts that make up the area. The district's elevation ranges from 50 to 60 m above sea level (amsl). Paithalmala is the most elevated point in the

Kannur District (1372 m), with over half of its inhabitants living in metropolitan zones. Kannur has an approximate population of 26 lakhs. The highest temperature is over 35°C , while the lowest temperature is about 20°C . The annual average rainfall is 34–38 mm. There are different soil types, i.e. lateritic soil, coastal alluvium soil, riverine alluvium, brown hydromorphic soil, and forest loam. The geography, geology, soils, climate, and natural vegetation all contribute to the physical characteristics. The area is defined geologically by Archean crystalline rocks, the majority of which are Chernockites. Coastal and alluvium, sand stone, and clay with intercalation make up the coastal area. The district has three reservoirs which serve as surface water irrigation sources (CGWB, 2007). The study area map is as shown in Fig. 1.

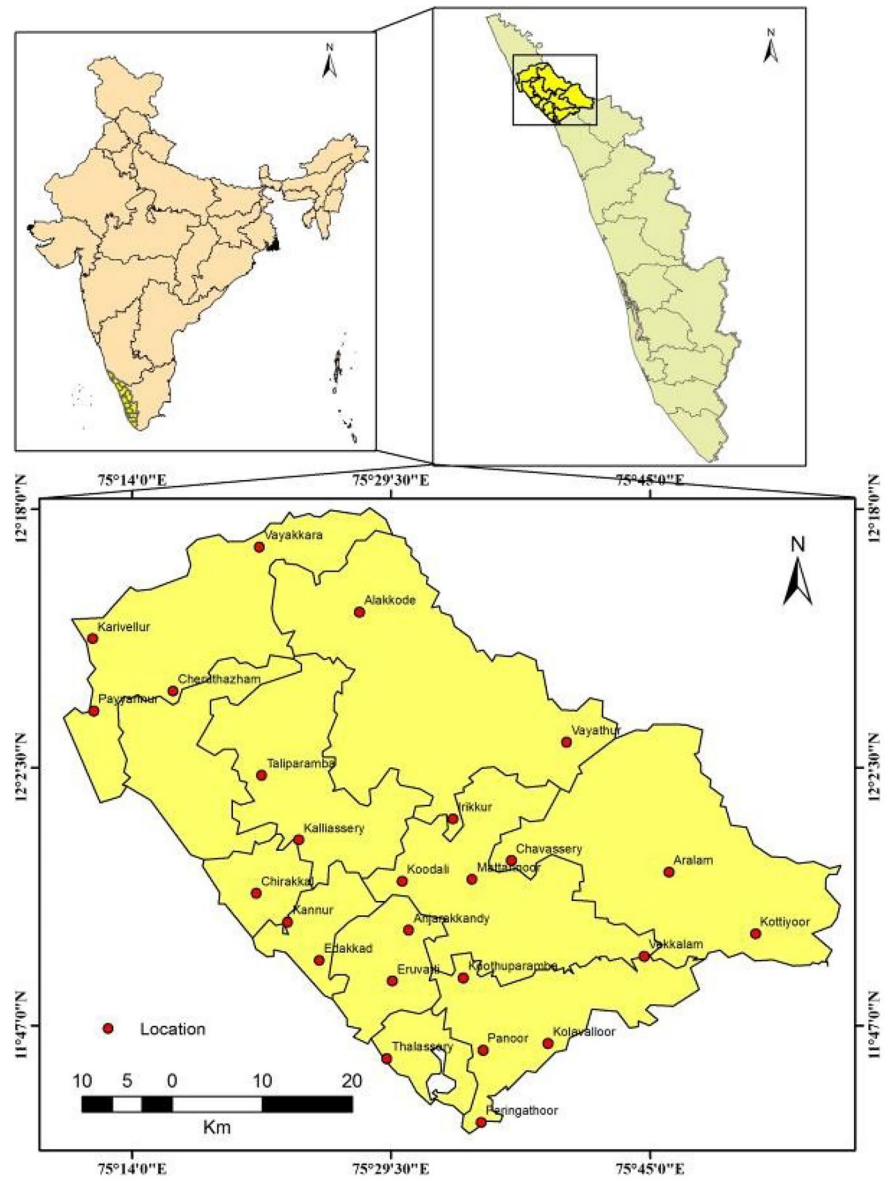
Groundwater data used

Groundwater samples were collected from the Kozhikode-based Centre for Water Resources Department and Management (CWRDM). In 2011, 25 area samples were obtained from the investigation zone. For 2019, 25 groundwater field samples were collected and done with physicochemical analysis in the Kannur University laboratory. The physico-chemical estimation of the 25 locations in 2011 and 2019 was not statistically significant between the two seasons.

Groundwater sampling collection and analysis

The groundwater samples from various bore wells were collected from the lower parts of wells in five taluks (Thalassery, Kannur, Iritty, Taliparamba, and Payyanur) in rural regions and close to industrial zones. The groundwater samples were collected in a clean 1-L plastic container and examined at the laboratory. The samples were examined by the American Public Health Association (APHA) 2005 using established procedures (2005). The investigation was carried out for physicochemical parameters. The testing locations were used to measure the geographical coordinate system with the help of global positioning system (GPS). The physicochemical parameters such as hydrogen ions (pH), electrical conductivity (EC), total dissolved solids (TDS), and significant cations and total hardness (TH), sodium carbonate (CO_3^-), bicarbonate (HCO_3^-), chloride (Cl^-), sulphate (SO_4^{2-}), nitrate (NO_3^-), calcium (Ca^{2+}), magnesium (Mg^{2+}), sodium (Na^+), potassium (K^+), and iron

Fig. 1 Study area map of Kannur district



(Fe^{2+}) these anions were used to analyse the laboratory analysis. It was examined by the standard methodology followed by APHA (2005).

The pH metre was used to test the water for hydrogen ions. A water analyser was used to determine the EC and TDS levels (Microprocessor pH-EC-TDS Meter – 1615). Turbidity was measured using a turbidity metre (Spectralab Model NT 4000 Turbidity Meter). EDTA was used to monitor the concentration rather than control the water quality parameters in TH, Ca^{2+} , and Mg^{2+} . Chloride was measured by

silver nitrate titration. Carbonate and bicarbonate were analysed by standard titrimetric analysis; sulphate was dissected utilising a Nephelometer (Systronics 132). Nitrate was investigated using the Ion Selective Electrode Method (V-780 UV-Visible/NIR Spectrophotometer). Iron was determined using the Colorimetric Thiocyanate Method, whereas sodium and potassium were determined using a flame photometer (Microprocessor Flame Photometer S-935) compound test. For this study, statistical analysis was used to investigate the relationships between various chemical characteristics.

The level of the water table affects the activity of groundwater everywhere around it. The results also include the extent of each limit, as well as insights and comments on groundwater quality. The study area map is presented in Fig. 1.

Multivariate statistical analysis

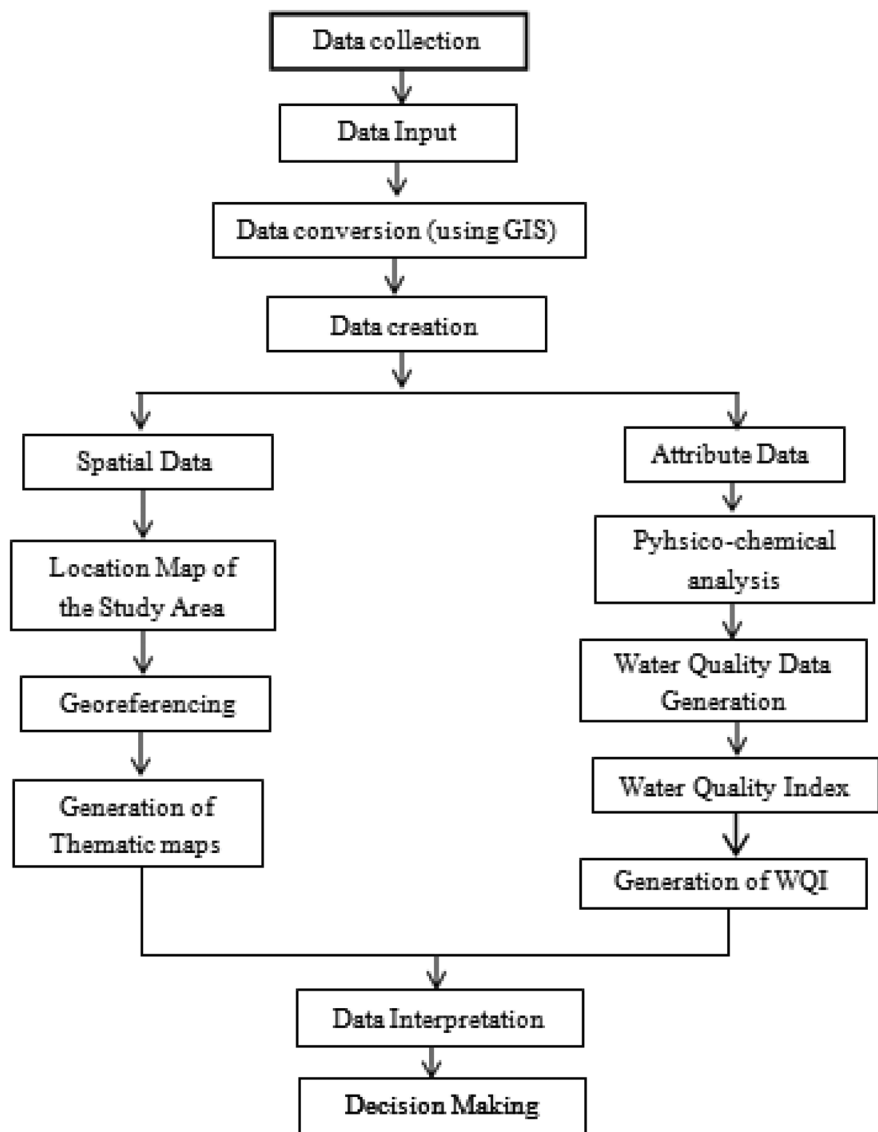
Multivariate statistical approaches such as descriptive statistics, principle components analysis, cluster analysis, correlation matrix analysis, and Pearson Correlation bivariate one tailed analysis were used in the SPSS

20 version environment to identify in groundwater sources. Figure 2 shows the entire study approach in a flow chart.

Descriptive statistics

A statistical analysis of data collected for groundwater quality parameters from 25 sample locations between 2011 and 2019 was performed. Descriptive statistical analysis, such as mean, median, average, standard error, dispersion, deviation, skewness, and kurtosis, is used to acquire a basic understanding of the sample distribution.

Fig. 2 The flow chart depicts the study’s overall methodology



Principal component analysis

Principal component analysis (PCA) is one of the most widely used statistical analysis techniques for analysing data patterns (Salem et al., 2022). This method for reducing groundwater data and separating a few unknown elements in order to examine links between the known factors (Farnham et al., 2003; Gou et al., 2007). PCA was used to remove the principal component (PC) from the data set and determine the geographical variations of physicochemical features in groundwater that are uncorrelated, or orthogonal in component. The first principal component (F1) absorbs and accounts for the largest possible percentage of the overall variation in the set of data, while the second component (F2) receives and provides for the variance. The percentage contribution of F_i to the overall variance in the normalised informative index, for example, is given by the formula 1.

$$\text{Percentage variance accounted by } F_i = \lambda_i / \sum \lambda_i \quad (1)$$

The quantity of factors in the informative collection is equal to the sum of the latent roots of all the main components, i.e. $\sum \lambda_i = \text{number of variables}$. Because the main component approach extracts the highest feasible variance for each preceding F_i , the values of latent roots get lower for future F_i 's.

F_i is a linear combination of the initial variables, as follows:

$$F_1 = b_{11} Y_1 + b_{12} Y_2 + b_{1K} Y_K$$

$$F_2 = b_{21} Y_1 + b_{22} Y_2 + b_{2K} Y_K$$

$$\lambda_i = b_{i1} Y_1 + b_{i2} Y_2 + b_{iK} Y_K$$

In the above expressions, b 's are factor loadings, Y 's are the original variable's standardised values, and ' k ' is the number of variables in the above expressions. A significant association between the variable and the factor is indicated by high factor loadings (values near to 1). Kaiser–Meyer–Olkin (KMO) and Bartlett's tests are used to assess the appropriateness of the PCA data set. KMO is a statistic for sample adequacy. If the KMO value is more than 0.5, a PCA can be performed. Bartlett's test of sphericity

is used to test the null hypothesis that the variables in the population correlation matrix are related and that the correlation matrix is an identity matrix. If the observed significance level is less than 0.05, the null hypothesis is rejected. It illustrates the existence of significant correlations between variables. Sundaray et al. (2006) used PCA on the normalised data sets and sorted those with Eigen values more than 1.0, which are regarded as having significant influence on hydro-geochemical processes in this study.

Hierarchical cluster analysis

Hierarchical cluster analysis (HCA) was used to classify the based on uniformity within a class and differences between classes (Mendiguchía et al., 2004; Han et al., 2006). It is essential for analysing data and identifying patterns. Because each ingredient of groundwater resources uses a unique approach, sample data must be normalised. Data standardization ensures that all variables in the study have almost the same impact (Rahman et al., 2014). It is most commonly used by a dendrogram to establish natural proximity links between any one sample and the entire informative collection (McKenna, 2003). The dendrogram provides a strategic distance from misclassification owing to huge variances in information dimensionality. It was employed to modify trial data using a z-scale change (Liu & Yang, 2018). The following Eq. (2) was used to normalise the data to the Z score ($m=0$ and $S=1$):

$$Z = (X - m)/S \quad (2)$$

where Z represents the standardised value, X represents the sample data value, m represents the mean, and S represents the standard deviation (Rahman & Gagnon, 2014).

Correlation matrix analysis

The statistical analysis was performed using standard techniques, which included calculating correlation coefficients between different parameter variables or between the objects on which these variables were assessed (Davis, 2002). The correlation coefficients were used to identify the closely related components and associated water quality metrics.

Pearson correlation bivariate one tailed analysis

The study was investigated the connections between various groundwater physicochemical assessments. The mean and standard deviation of each measurable parameter were computed twenty-five sample locations. Pearson correlation is a way of analysing the relationship between two variables that indicates that changes in one are connected to changes in the other (Pallant, 2011). Once a correlation is created, the rest of the parameters may be determined simply by measuring a few significant parameters, and the rest of the parameters can be assessed quickly and easily (Patil & Patil, 2010). Once a correlation is established, the remaining parameters may be found simply by monitoring a few relevant values, and the remaining parameters can be assessed fast and easily (Patil & Patil, 2010). SPSS software was used for the statistical analysis, with confidence intervals of 0.05 and 0.01. The Pearson product moment correlation coefficient was calculated using Eq. (3) (Kumar & Riyazuddin, 2008).

$$r^2 = \frac{n \sum xy - \sum x \sum y}{[n \sum x^2 - (\sum x)^2][n \sum y^2 - (\sum y)^2]} \tag{3}$$

The coefficient of determination (r^2) was calculated to explain both changes in one variable and changes in the other. HCA has been effectively used in many studies to examine and analyse groundwater quality data (Kumar & Riyazuddin, 2008; Rani & Babu, 2008). HCA was performed on a standardised data set to reduce the impact of data measurement scale.

Spatial interpolation techniques of groundwater using GIS

The groundwater information about different areas was utilised for the spatial interpolation technique. For example, kriging, inverse distance weighted (IDW), and spline techniques were used to predict and measure the geographic variation of the groundwater dataset. Apart from this study, many researchers implement the same methodologies across a wide range of topics. The method was used in groundwater-related studies and has a wide range of regional and international applications. The IDW technique was chosen for this study’s spatial analysis because of its efficacy and estimate accuracy when compared to other relation approaches such

as kriging and spline (Courault & Monestiez, 1999; Gorai & Kumar, 2013). The spatial analyst-interpolation module system was attempted using the ArcGIS environment tool (Thangavelu, 2013). The IDW method is used as it handles spatially interpolated data precisely. In Eq. (4), Mitas and Mitasova (1999) used the IDW technique in a linear direction.

$$Z_j = \frac{\sum_{i=1}^n \frac{Z_i}{(h_{ij} + \delta)^\beta}}{\sum_{i=1}^n \frac{1}{(h_{ij} + \delta)^\beta}} \tag{4}$$

In the equation, Z_j is the result at an ungauged location, Z_i is the available data, is the weight, and is a flattening factor, and h_{ij} is the spacing interval here between predictable and unpredictable point (5).

$$h_{ij} = \sqrt{(\Delta x)^2 + (\Delta y)^2} \tag{5}$$

where x and y are the reference axis distances between the unknown point j and the sampled point i .

Assessment of water quality index

The water quality index (WQI) is a mathematical approach used to integrate a large quantity of data on water quality into a measure that indicates the extent of contamination (Singh et al., 2013). It is a simple method for determining the quality of water. The suitability of drinking water is determined by comparing the water quality data from the samples tested to the BIS (2012) recommended drinking water standard, which is used to calculate the WQI (Verma et al., 2020). It assists with expressing the present situation of water to public entities and decision-makers involved in water management (Alam et al., 2020; Balamurugan et al., 2020). A single number reflects an index that takes into account all of the elements that impact water quality (Vasanthavigar et al., 2010). Equation (6) gives the formula for the water quality index.

$$WQI = \frac{\sum_{i=1}^n q_i w_i}{\sum_{i=1}^n w_i} \tag{6}$$

$$q_i = 100 \times \frac{V_i}{S_i}$$

where q_i is the Sub Index, and V_i is the observed value in the lab, n is the number of parameters taken, S_i is

the typical value of i th particle, and w_i is the weight of i th parameter.

Results and discussion

Multivariate statistics analysis of groundwater parameters

Descriptive statistical analysis

The statistical variables range, minimum, maximum, median, standard deviation, variation, skewness, and kurtosis were examined in descriptive statistics in Tables 1, 2, and 3. The pH values of ground water between 2011 and 2019 range around 5.30 and 4.2. 2011 has a minimum pH value of 3, and 2019 has a minimum pH value of 3.7. The maximum value is represented in 2019 (8.3), and in 2011 it became 7.9 in 2019. The mean value in 2011 was 6.9, and in 2019 it is 6.52, despite the fact that the mean value in 2011 was extremely high. The standard deviation of 2011 (1.52) is highly presented when comparing the year of 2011 (0.96). The variance in 2011 was 1.48, while the variance in 2019 was 0.92, indicating that the variance in 2019 is well represented. The skewness of 2011 (−1.58) and 2019 is −1.09, when discussing highly observed in 2011. The kurtosis value of 2011 is presented at 3.13 and that of 2019 is observed at 1.76, whereas comparing the kurtosis highly observed in the year of 2011 is shown in Fig. 3. The standard deviation of 2011 (1.52) is highly presented in the year of 2011 (0.96).

The variance of 2011 is observed at 1.48 and the variance of 2019 is presented at 0.92. The skewness of 2011 (−1.58) and 2019 is −1.09, whereas the comparison was highly observed in 2011. The kurtosis value of 2011 is presented at 3.13, and in 2019 it is observed at 1.76. It was highly observed in the year 2011 as shown in Fig. 3. As shown in Fig. 4, electrical conductivity, total hardness, total dissolved solids, carbonate, bicarbonate, chloride, sulphate, nitrate, calcium, magnesium, sodium, potassium, and iron were all dissolved in descriptive statistics in the same way as the previously mentioned (for example, pH) and separately. The World Health Organization (WHO, 2006), the Bureau of Indian Standards (BIS, 2003), and the United States Environmental Protection Agency (USEPA, 1975) standards were compared to physicochemical parameters for drinking

purposes of groundwater. Modifying traditional cropping types and introducing drips, sprinklers, and micro-irrigation technologies to decrease groundwater depletion may be advantageous in some areas to avoid groundwater depletion, according to the study. The findings show that the recommended limits in Table 1 are the most important factors to consider when comparing groundwater samples.

Principal component analysis

A groundwater quality study was performed in 2011 and 2019 using principal component analysis (PCA) with Varimax rotation and Kaiser Normalization component values. According to Kaiser (Liu & Yang, 2018), only factors with eigenvalues bigger than one should be considered. In the 2011 and 2019 data sets, the KMO measure of sample adequacy is 0.846, and the importance level of Bartlett's trial of sphericity is 0.001. To improve groundwater management, we need to focus on more than the quantity of water aquifers can provide. Many of the location's major aquifers have been losing groundwater, particularly in the nearby Kannur region. PCA was performed on normalised data sets, including fourteen water quality standards. Figure 5a and b shows that in 2011, four variables with eigenvalues larger than accounted for 84.7% of the absolute change in the data set. Four variables in the 2019 informative ranking have eigenvalues larger than one, accounting for 73.4% of the data set's overall variability. Figure 6a and b shows the factor loadings created by varimax symmetrical rotation from the 2011 and 2019 data sets, respectively.

The PC loadings indicate both positive and negative relationships. The loadings approaching 1 indicate a significant relationship between the variable and the PC. A strong link has a PC value that is greater than 0.75. The values between 0.5 and 0.74 were determined to be closely connected. The processes that have been interpreted based on the factor loadings are shown in Table 2a and b. The eigenvalues were highly presented in 2011. Table 3 used scree plots to determine the number of PCs in order to understand the groundwater parameter structure. The overall variation for PC1, PC2, PC3, and PC4 for groundwater quality data in 2011 was 34.84%, 20.76%, 19.25%, and 9.81%, respectively. The factor (PC1) in the data sets showed that it was highly positively loaded with all of the physicochemical characteristics in 2011.

Table 1 Descriptive statistics of the research area's physico-chemical characteristics with WHO and BIS limits (2011 and 2019)

Para Meters	N	Range		Minimum		Maximum		Mean		Std. Dev		Variance		Skewness		Kurtosis		Standards		
		2011	2019	2011	2019	2011	2019	2011	2019	2011	2019	2011	2019	2011	2019	2011	2019	BIS	WHO	USEPA
pH	25	5.30	4.2	3	3.7	8.30	7.9	6.90	6.52	1.22	0.96	1.484	0.92	-1.58	-1.09	3.136	1.76	6.5	6.5	-
EC	25	474	368	31	35	505	403	169.12	163.68	120.16	97.74	14,439.4	9552.64	0.99	1.08	0.774	0.95	300	500	-
TH	25	166.6	174	15.15	14	181.8	188	57.33	59.92	43.38	42.89	1881.67	1839.16	1.51	1.50	1.917	2.65	200	0.3	200
TDS	25	284.4	246	18.6	22	303.0	268	101.47	109.30	72.10	59.51	5198.20	3541.84	0.99	0.85	0.774	1.02	500	500	-
CO ₃	25	12	5	0	0	12	5	1.12	1.05	2.90	1.61	8.42	2.60	2.76	1.46	7.420	1.01	75	75	-
HCO ₃ ⁻	25	175.7	202.46	0	10.69	175.7	213.1	46.66	63.56	44.60	56.16	1989.09	3154.08	1.36	1.31	1.519	1.02	30	150	-
Cl ⁻	25	53.71	25.52	5.75	0	59.46	25.52	24.86	8.39	17.12	8.00	292.99	63.99	1.20	0.90	-0.021	-0.58	250	250	250
SO ₄ ²⁻	25	30.6	99	0	1	30.60	100	4.33	19.80	6.88	24.75	47.35	612.51	2.84	2.36	8.896	4.93	200	250	250
NO ₃	25	3.47	2.00	0	0.001	3.47	2.00	1.08	0.48	1.08	0.62	1.16	0.38	1.28	1.37	0.624	0.55	45	50	-
Ca ²⁺	25	46.05	156	1.62	4	47.67	160	13.14	37.68	11.91	38.06	141.73	1448.89	1.61	2.33	2.275	5.49	75	100	-
Mg ²⁺	25	15.22	58	0	4	15.22	62	5.96	21.84	3.99	14.07	15.92	197.97	0.76	1.12	-1.170	1.29	5.96	50	-
Na ⁺	25	25.7	4.8	2.80	.6	28.50	5.4	11.78	1.70	8.42	0.97	70.97	0.94	0.93	2.33	-4.22	8.31	50	200	-
K ⁺	25	17.9	1.2	0.10	0	18.0	1.2	4.26	0.48	4.47	0.31	19.99	0.10	1.39	0.30	2.099	-0.45	-	200	-
Fe ²⁺	25	3.79	4.65	0	0	3.79	4.65	0.57	0.96	0.89	1.48	0.80	2.20	2.55	1.50	6.785	0.85	-	200	0.3

Table 2 (a, b) Varimax with Kaiser normalization rotated method factor loadings from PCA of standardised water quality data (2011 and 2019)

2a) Principal component (2011)				
Variable	PC1	PC2	PC3	PC4
pH	0.814	0.119	0.658	0.162
EC	0.641	0.336	-0.089	-0.056
TH	0.719	0.225	0.095	-0.254
TDS	0.651	0.333	-0.089	-0.056
CO ₃ ⁻	0.312	0.691	0.611	-0.121
HCO ₃ ⁻	0.411	0.571	0.647	-0.19
Cl ⁻	0.443	0.242	-0.611	0.208
SO ₄ ²⁻	0.624	0.272	-0.178	0.362
NO ₃ ⁻	0.431	0.164	-0.775	-0.093
Ca ²⁺	0.643	0.262	0.206	-0.291
Mg ²⁺	0.512	0.634	-0.121	-0.145
Na ⁺	0.451	0.336	-0.297	0.348
K ⁺	0.522	0.398	-0.048	0.186
Fe ²⁺	0.072	0.065	0.543	0.697
Eigen value	4.692	3.093	2.698	1.076
% of variance	34.843	20.766	19.254	9.814
Cumulative %	34.843	55.609	74.864	84.678
2b) Principal component (2019)				
Variable	PC1	PC2	PC3	PC4
pH	0.193	0.819	-0.188	-0.261
EC	0.733	-0.325	-0.168	-0.246
TH	0.814	0.471	0.175	-0.148
TDS	0.807	-0.345	-0.16	-0.187
CO ₃ ⁻	0.079	0.336	0.648	0.241
HCO ₃ ⁻	-0.251	0.551	-0.073	0.541
Cl ⁻	0.628	-0.099	-0.105	-0.143
SO ₄ ²⁻	0.337	0.279	0.567	-0.102
NO ₃ ⁻	0.183	-0.467	0.656	0.297
Ca ²⁺	0.807	0.28	0.332	-0.255
Mg ²⁺	0.302	0.649	-0.334	0.213
Na ⁺	0.651	-0.509	-0.024	0.503
K ⁺	0.727	-0.204	-0.375	0.401
Fe ²⁺	-0.471	-0.423	0.101	-0.441
Eigen value	4.413	2.816	1.68	1.369
% of variance	31.524	20.117	12.001	9.777
Cumulative %	31.524	51.641	63.643	73.417

Bold values are represents strong (>0.75), and moderate (0.75-0.50) loading factor

The factor (PC1) pH shows a very high positive correlation and a moderate correlation with TH, EC, TDS, SO₂⁻, Ca²⁺, Mg⁺, and K⁺ parameters in 34.84% of the total variance. EC stands for salt concentration and is a good indicator of accessible nutrients.

Calcium includes largely dissolved mineral elements, and hardness considerably affects the value of water for public and industrial uses. The study found that factor (PC1) causes groundwater dilution, with TDS, chloride, and sulphate concentrations in groundwater slightly lower than the other parameters in the 2011 samples. PC2 is moderately linked with CO₃⁻, HCO₃⁻, and Mg²⁺ and discloses 20.7% of the variability. The clusters of site-specific samples in space and their spatial distribution are confirmed by the PCs scores plot created using PC1 and PC2 components.

PC2 demonstrates the use of the physicochemical limit. CO₃⁻, HCO₃⁻, and Mg²⁺ are delivered to groundwater because of the disintegration of minerals bearing these particles during the stimulation of spring by precipitation. PC3 accounts for 19.2% of the data set's variance and includes moderate positive correlations with pH, CO₃⁻, HCO₃⁻, and Fe²⁺, all of which are explained by combining multiple sources. Nitrate is negatively highly correlated, and Cl⁻ is moderately correlated, with variability reduced in groundwater samples. Two separate processes have been proposed for this, with bicarbonate indicating intense weathering of carbonate settings and groundwater's alkaline character. PC4 has iron loadings and accounts for 9.8% of the variability. The loading of Fe has a positive relationship and is linked to the decomposition of organic materials by iron reduction. The scree plot (Fig. 6b) is excellent for detecting a number of positive components with a significant scale difference. For PC1, PC2, PC3, and PC4, the overall variance of groundwater quality data in 2019 was 31.52%, 20.11%, 12%, and 9.77%, respectively. The majority of the samples have visible grouping in the upper left and lower left quadrants, but sample loading in the upper right and lower right quadrants is significantly scattered.

PC1 reports 31.5% of the variance, elucidating that TH, TDS, and Ca were strongly positive correlated. The loadings EC, K⁺, Na⁺, and Cl⁻ are in moderate correlation. The loading of TH, TDS, Ca²⁺, EC, K⁺, Na⁺, and Cl⁻ comes from various sources, including groundwater salinity and the application of chemical fertilisers in agricultural fields. As a result, the study location was not far from salinity-affected areas along the neighbouring Valapattanam river system. PC1 illustrates the distribution of the physico-chemical parameters TH, TDS, Ca²⁺, EC, K⁺, Na⁺, and Cl⁻, indicating that residential waste water seeping from on-site sanitation systems has contaminated groundwater. PC2 is responsible for 20.1% of the variability and includes

Table 3 Correlation coefficient matrix of various groundwater quality parameters (2011)

Parameters	pH	EC	TH	TDS	CO ₃	HCO ₃	Cl	SO ₄	NO ₃	Ca	Mg	Na	K	Fe
pH	1	-	-	-	-	-	-	-	-	-	-	-	-	-
EC	-0.05	1	-	-	-	-	-	-	-	-	-	-	-	-
TH	0.432	0.481	1	-	-	-	-	-	-	-	-	-	-	-
TDS	-0.188	0.896	0.45	1	-	-	-	-	-	-	-	-	-	-
CO ₃ ⁻	0.044	-0.109	0.3	-0.123	1	-	-	-	-	-	-	-	-	-
HCO ₃ ⁻	0.198	-0.343	-0.146	-0.503	0.201	1	-	-	-	-	-	-	-	-
Cl ⁻	0.083	0.342	0.431	0.415	-0.121	-0.275	1	-	-	-	-	-	-	-
SO ₄ ²⁻	0.214	0.103	0.349	0.042	0.161	-0.022	0.014	1	-	-	-	-	-	-
NO ₃ ⁻	-0.46	0.067	0.073	0.101	0.262	-0.232	0.136	0.246	1	-	-	-	-	-
Ca ²⁺	0.277	0.49	0.937	0.485	0.27	-0.266	0.469	0.43	0.182	1	-	-	-	-
Mg ²⁺	0.498	0.071	0.369	-0.001	0.138	0.259	0.009	-0.124	-0.263	0.025	1	-	-	-
Na ⁺	-0.489	0.537	0.076	0.582	-0.039	-0.223	0.345	0.033	0.476	0.152	-0.182	1	-	-
K ⁺	-0.077	0.559	0.226	0.51	-0.262	-0.185	0.432	-0.14	0.177	0.207	0.093	0.807	1	-
Fe ²⁺	-0.088	0.593	0.245	0.83	-0.264	-0.171	0.481	-0.04	0.299	0.323	0.116	0.493	0.933	1

The bold prominences on when r values were more than +0.75 are strongly positive correlated

pH-related factors. The moderate positive association of Mg⁺ with CO₃⁻ means that Mg increases as the magnesium concentration of groundwater in dissolved condition with deposits of salts in the study area. The sample characteristics are represented in the PCs score plots, which help in understanding their spatial distribution.

PC3 in the data sets have 12% of variability, which are CO₃⁻, SO₂⁻ and NO₃⁻, which comprise three parameters moderately positive. Non-carbonate hardness scale is hard and difficult to remove, but carbonate hardness scale

is porous and easy to remove. The increased amount of soap or detergent needed to generate a lasting lather is usually a sign of hardness in the water. As the hardness of the water increases, so does the amount of soap used, resulting in a disagreeable curd. However, the factor loading of NO₃⁻ is non-significant; PC3 shows that evaporation is not a main factor determining Cl⁻ concentrations in groundwater. Anthropogenic pollution from onsite sanitation, livestock waste, and municipal landfill sites may be identified as another source of nitrate process, and it is desirable to dilute NO₃⁻ concentrations

Fig. 3 The study area's total physico-chemical analysis (2011)

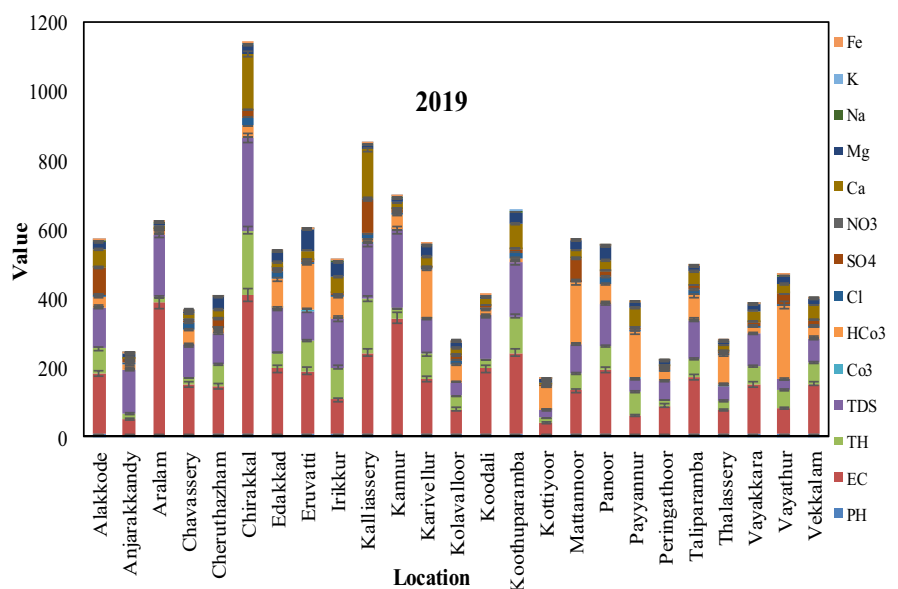
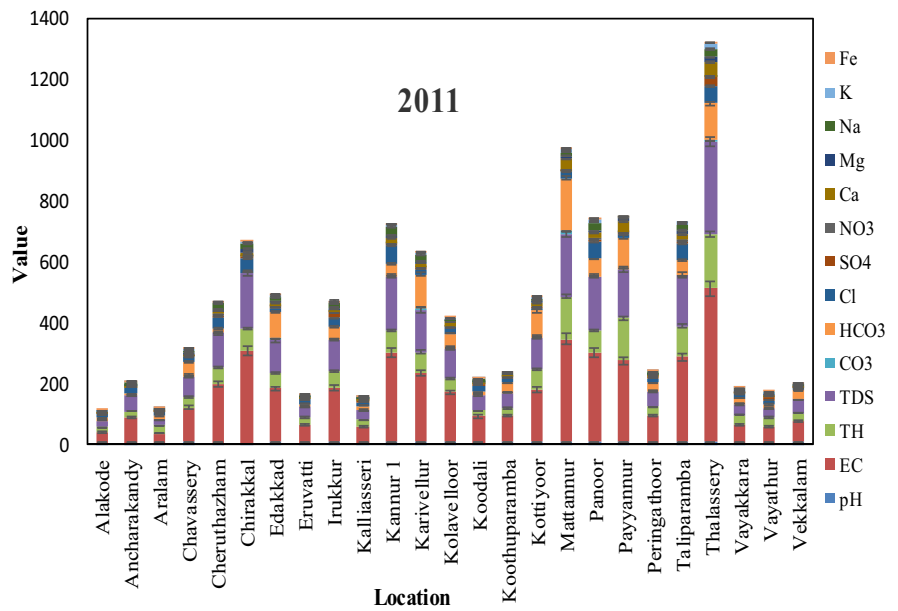


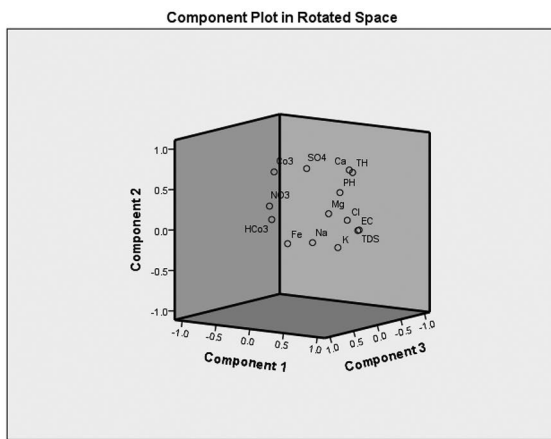
Fig. 4 The study area's total physico-chemical analysis (2019)



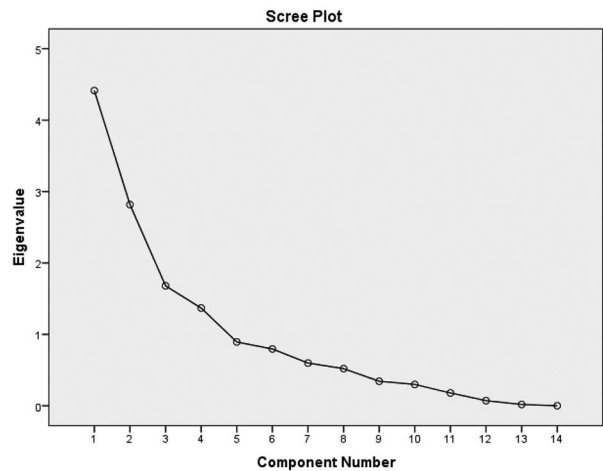
to reduce them. PC3 and PC4 show that the strong and positive loadings by one parameter with an insignificant proportion of variance (i.e. 12 and 9.7%, respectively) were given the least advantage in regulating groundwater chemistry. PC4 has 9.7% variability in the data sets and is made up of two factors, HCO_3^- and Na^{2+} , which has a bit positive relationship. The bicarbonate content of groundwater causes a rise in Na^+ value, which might cause organic matter in the soil to dissolve.

Hierarchical cluster analysis

Groundwater samples from various classes were used in a hierarchical cluster analysis. Squared Euclidean distances were employed to quantify item similarity, and a dendrogram employing the Centroid linkage method of hierarchical clustering was used for cluster analysis (CA). The dendrograms are made up of multiple clusters, each of which contains one or



(a)



(b)

Fig. 5 Component plot in rotated space (a) and scree plot of the characteristic eigenvalues (b) are used in principal component analysis (2011)

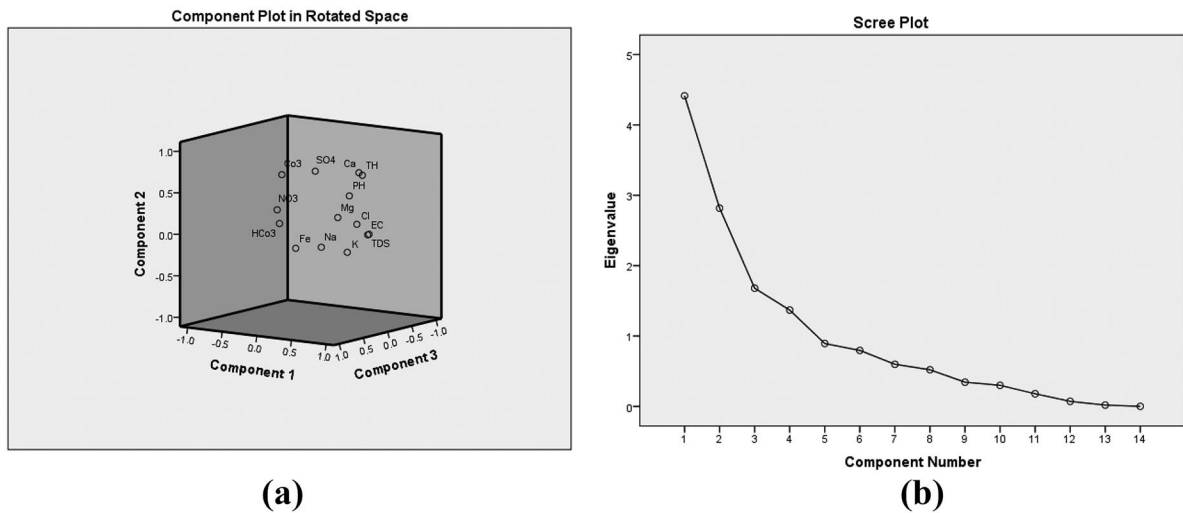


Fig. 6 Component plot in rotated space (a) and scree plot of the characteristic eigenvalues (b) are used in principal component analysis (2019)

more variables. Clusters are chosen for easier understanding based on a visual analysis of the dendrogram Fig. 7a and b. CA created five types of cluster groupings by combining groundwater samples from the study region in 2011 and 2019. In 2011, EC and Ca^{2+} were in Group I, TDS and Na^+ were in Group II, TH and HCO_3^- were in Group III, Mg^{2+} and Cl^- were in Group IV. The weathering of parent rocks, ion exchange processes, and salt leaching from the rocks are the main sources of increasing Ca, Mg, and Cl concentrations in groundwater. Permanent hardness has been recognised as an issue in the study area, necessitating advanced treatment methods such as reverse osmosis, base ion exchange, and desalination procedures to treat groundwater before use. K^+ , Fe^{2+} and SO_4^- were in Group V, NO_3^- was in Group VI, and CO and pH were in Group VII. In 2019, Group I included NO_3^- , K^+ , Na^+ , Fe^{2+} , CO_3^- , pH, and Ca^{2+} ; Group II included Cl^- and SO_4^- ; Group III included Mg; Group IV included HCO_3^- and TDS; and Group V included TH and EC. Extreme values in the data sets are sensitive to the clusters. The similarity between PCA factors and HCA clusters supports the PCA-suggested dominating processes.

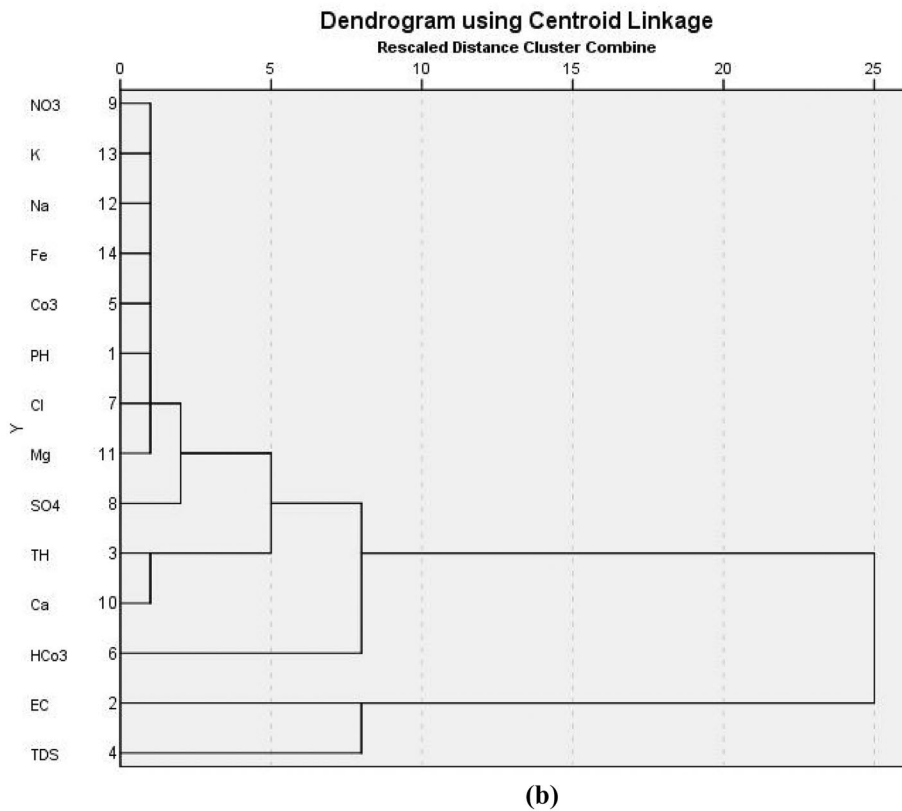
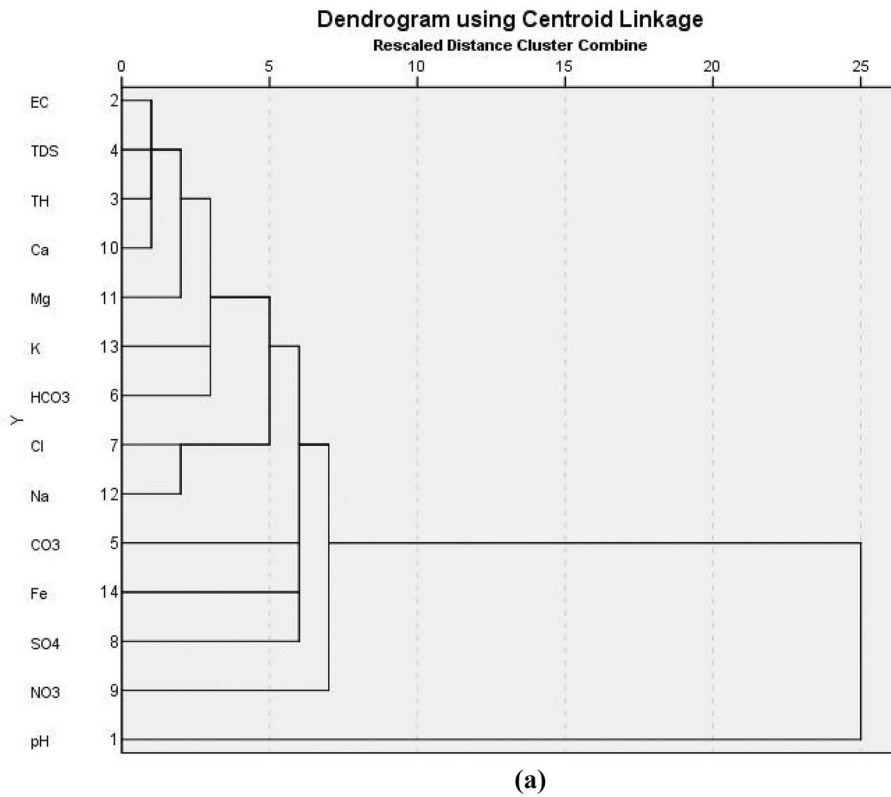
Correlation coefficient matrix analysis

In most cases, the correlation coefficient is used to quantify the relationship between the two variables.

The values were evaluated for the ground water quality zones shown in Table 3. There is a direct relationship when the parameters of one of the region’s variables increase or decrease. In the resultant, the aftereffects of the relationship evaluation are taken into account. A high correlation coefficient (1 or –1) indicates a strong relationship between two parameters, whereas a connection coefficient of zero indicates no relationship. Positive values suggest a positive relationship, while negative “r” estimations indicate the opposite.

In 2011, the results show that a highly positive correlation is observed between calcium and total hardness (0.967), TDS and TH (0.926), TH and EC (0.926), Mg^{2+} and TH (0.888), Na^+ and Cl^- (0.882), K^+ and EC (0.861), HCO_3^- and TH (0.781), CO_3^- and TH (0.482), SO_4^- and EC (0.558). Ca^{2+} has a highly significant correlation with TDS, Mg^{2+} , HCO_3^- and CO_3^- , it conveyed that increases in rainfall infiltrate rate, sewage water intrusion, and uncovered septic tank increases nitrate level in groundwater respectively. TH, K^+ and SO_4^- have low positive correlations between TH and EC, indicating that changes in the direct correlation of conductivity increase as the concentration of ions increases and electrical conductivity values can be measured in low quality water.

All of the sample locations have Na^+ values below the allowed limit of 200 mg/L. In all of the sample locations, the sulphate concentration in groundwater in the study region was below the acceptable limit of 400 mg/L. For this, a matrix analysis of Cl^- is



◀**Fig. 7 a** Hierarchical cluster analysis (2011). **b** Hierarchical cluster analysis (2019)

performed, and a highly negative relationship between pH and Cl^- (-0.025) is observed, demonstrating that changes in hydrogen particle fixation resolve the direct correlation of Cl^- in groundwater. NO_3^- was acquired with an exceptionally helpless negative connection between pH (-0.339), demonstrating that the immediate relationship of Cl^- in water is unique. About a quarter of the sample locations surpass the 300 mg/L permissible limit. Around 50% of the sample locations in the study region have nitrate concentrations above the maximum allowable in groundwater. Despite a low negative relationship with Cl^- (-0.145), it is clear that higher fixation is observed in groundwater. It might be linked to groundwater contamination sources from storm basement rocks or anthropogenic sources of salinity level in the study area, as shown in Table 3.

In 2019, the results show that Fe^{2+} has a highly significant correlation with K^+ (0.963), indicating that it has lower geochemical mobility in groundwater samples, rich fertilisers in agricultural field for increasing the crop yield. Ca^{2+} has a highly positive correlation with total hardness (0.896); K^+ has a positive significant correlation with Na^+ (0.807), indicating that it is affected by drainage water seepage into the groundwater aquifer and salt dissolution in soil; TDS has a strong positive correlation with EC (0.896). TH has a minimum positive connection with EC (0.481),

despite the fact that it is dependent on ion mobility in water. Cl^- and SO_4^{2-} have low positive correlations with total hardness (0.431 and 0.349, respectively), indicating the hardness and scale-forming properties of water; NO_3^- have low positive correlation with CO_3^{2-} (0.262) which indicates that rock water interaction and weathering of parental rock contribute to elevate the concentration of nitrate in groundwater; and Mg^{2+} have a low positive correlation with pH (0.498). The conductivity values tested in low quality water had a strong negative connection with CO_3^{2-} and HCO_3^- . Table 4 shows the Na^+ concentration for the low negative correlation with pH (-0.489).

Pearson correlation bivariate one tailed analysis

The groundwater testing showed a strong ($p < 0.01$) and large ($p < 0.05$) relationship. The Pearson correlation result for pH ($r=0.325$), TDS ($r=0.25$), CO_3^{2-} ($r=0.106$), HCO_3^- ($r=0.297$), SO_4^{2-} ($r=0.246$), Mg^{2+} ($r=0.133$), Na^+ ($r=0.226$), and K^+ ($r=0.246$) in 2011 is provided in Table 5. Groundwater testing found a strong ($p < 0.01$) and a positive correlation ($p < 0.05$). As shown in Table 5, the Pearson correlation output has a high level of confidence in pH ($r=0.325$), TDS ($r=0.25$), CO_3^{2-} ($r=0.106$), HCO_3^- ($r=0.297$), SO_4^{2-} ($r=0.246$), Mg^{2+} ($r=0.133$), Na^+ ($r=0.226$), and K^+ ($r=0.246$). Separately, with a 95% confidence level, the modest positive association of Ca^{2+} is noted with NO_3^- ($r=0.223$). It suggests that variations in NO_3^- are linked to calcium;

Table 4 Correlation coefficient matrix of various groundwater quality parameters (2019)

Parameters	pH	EC	TH	TDS	CO3	HCO3	Cl	SO4	NO3	Ca	Mg	Na	K	Fe
pH	1	-	-	-	-	-	-	-	-	-	-	-	-	-
EC	0.325	1	-	-	-	-	-	-	-	-	-	-	-	-
TH	0.418	0.926	1	-	-	-	-	-	-	-	-	-	-	-
TDS	0.325	0.906	0.926	1	-	-	-	-	-	-	-	-	-	-
CO_3^{2-}	0.406	0.436	0.482	0.436	1	-	-	-	-	-	-	-	-	-
HCO_3^-	0.707	0.671	0.781	0.671	0.797	1	-	-	-	-	-	-	-	-
Cl^-	-0.025	0.724	0.499	0.724	-0.030	0.065	1	-	-	-	-	-	-	-
SO_4^{2-}	0.246	0.558	0.551	0.558	0.040	0.243	0.464	1	-	-	-	-	-	-
NO_3^-	-0.339	0.475	0.337	0.475	-0.150	-0.150	0.682	0.359	1	-	-	-	-	-
Ca^{2+}	0.537	0.889	0.967	0.889	0.515	0.837	0.428	0.489	0.223	1	-	-	-	-
Mg^{2+}	0.133	0.832	0.888	0.832	0.339	0.545	0.540	0.567	0.485	0.740	1	-	-	-
Na^+	0.226	0.792	0.553	0.792	0.279	0.318	0.882	0.471	0.497	0.514	0.528	1	-	-
K^+	0.426	0.861	0.746	0.861	0.425	0.617	0.697	0.596	0.409	0.723	0.658	0.805	1	-
Fe^{2+}	0.346	0.073	0.044	0.073	0.357	0.321	-0.145	0.184	-0.352	0.010	0.098	0.119	0.149	1

The bold prominences on when r values were more than +0.75 are positively correlated

there is a weak positive correlation between Fe^{2+} and SO_4^{2-} ($r=0.184$). It denotes the presence of sulphate in iron. When a drop in NO_3^- (-0.15) is linked to a rise in carbonate levels in groundwater, the result is a negative correlation (Table 6).

The coefficient of determination for EC—pH ($r^2=0.105$) and TDS—pH ($r^2=0.325$) as shown in Tables 7 and 8, which indicates that changes in the level of TDS and EC (10.5%) are explained by changes in pH, respectively. CO_3^{2-} -pH ($r^2=0.011$), HCO_3^- -pH ($r^2=0.088$), SO_4^{2-} -pH ($r^2=0.061$), Mg^{2+} -pH ($r^2=0.017$), Na^+ -pH ($r^2=0.051$), K^+ -pH ($r^2=0.061$), while correlation with conductivity was strong but high respectively. The coefficients of correlation of Cl^- - HCO_3^- ($r^2=0.004$), Ca^{2+} - NO_3^- ($r^2=0.049$), and Fe^{2+} - SO_4^{2-} ($r^2=0.033$) are less positive, whereas NO_3^- - CO_3^{2-} ($r^2=0.022$) is negative. It means the presence of iron and manganese at an acceptable temperature is linked to groundwater turbidity. TDS, CO_3^{2-} , HCO_3^- , NO_3^- , Mg^{2+} , Na^+ , and K^+ levels all have a significant positive relationship with pH, NO_3^- , and SO_4^{2-} . Because nitrate interacts with ionic content in water, the minor negative correlation with carbonate is predictable. As shown in Table 7, nitrate and carbonate have modest negative correlations.

In 2019, the correlation analysis from the Pearson correlation output (Table 6) showed that pH has a strong correlation with SO_4^{2-} ($r=0.3267$) and Mg^{2+} ($r=0.151$); pH shows the low positive correlation with HCO_3^- ($r=0.233$), nitrate with CO_3^{2-} ($r=0.25$) and calcium with

CO_3^{2-} ($r=0.135$), sodium with SO_4^{2-} ($r=0.79$), and iron with NO_3^- (0.242) respectively. A negative correlation EC involves the decrease in pH (-0.052) and TDS with pH (-0.121) and is related to an increase in TDS levels in groundwater. This indicates that the existence of EC and TDS at an acceptable pH will be related to the groundwater as indicated in Table 6. The pH has a strong positive correlation with SO_4^{2-} -pH ($r^2=0.071$) and Mg^{2+} ($r^2=0.022$); pH has a weak positive correlation with CO_3^{2-} -TH (0.096), chloride with HCO_3^- ($r^2=0.054$), nitrate with CO_3^{2-} ($r^2=0.062$), calcium with CO_3^{2-} ($r^2=0.018$), sodium with SO_4^{2-} ($r^2=0.143$), iron with NO_3^- . A negative correlation EC involves that a decrease in pH (0.002) and TDS with PH (0.014) is related to an increase in TDS levels in groundwater as presented in Table 8. The pH has a critical negative relationship with the greater part of the physico-chemical characteristics. As a result, the chemical processes that take place in a groundwater system are highly involved. The correlation analysis provides accurate information about these complicated systems of water–rock interactions, as well as a broad knowledge of water–rock interactions.

Groundwater quality in Kannur district: an integrated geographical analysis

Spatial analysis is used to determine the quality of groundwater variation in the study area. The spatial variation of many groundwater physicochemical parameters, such

Table 5 Bivariate one-tailed Pearson correlation study of various groundwater quality metrics (2011)

Parameters	pH	EC	TH	TDS	CO3	HCO3	Cl	SO4	NO3	Ca	Mg	Na	K	Fe
pH	1	–	–	–	–	–	–	–	–	–	–	–	–	–
EC	0.325	1	–	–	–	–	–	–	–	–	–	–	–	–
TH	.418*	.926**	1	–	–	–	–	–	–	–	–	–	–	–
TDS	0.325	1.000**	.926**	1	–	–	–	–	–	–	–	–	–	–
CO_3^{2-}	.406*	.436*	.482**	.436*	1	–	–	–	–	–	–	–	–	–
HCO_3^-	.707**	.671**	.781**	.671**	.797**	1	–	–	–	–	–	–	–	–
Cl^-	–0.025	.724**	.499**	.724**	–0.03	0.065	1	–	–	–	–	–	–	–
SO_4^{2-}	0.246	.558**	.551**	.558**	0.04	0.243	.464**	1	–	–	–	–	–	–
NO_3^-	–.339*	.475**	.337*	.475**	–0.15	–0.15	.682**	.359*	1	–	–	–	–	–
Ca^{2+}	.537**	.889**	.967**	.889**	.515**	.837**	.428*	.489**	0.223	1	–	–	–	–
Mg^{2+}	0.133	.832**	.888**	.832**	.339*	.545**	.540**	.567**	.485**	.740**	1	–	–	–
Na^+	0.226	.792**	.553**	.792**	0.279	0.318	.882**	.471**	.497**	.514**	.528**	1	–	–
K^+	.426*	.861**	.746**	.861**	.425*	.617**	.697**	.596**	.409*	.723**	.658**	.805**	1	–
Fe^{2+}	.346*	0.073	0.044	0.073	.357*	0.321	–0.145	0.184	–.352*	0.01	0.098	0.119	0.149	1

* At the 0.05 level, the correlation is significant (1-tailed)

** At the 0.01 level, the correlation is significant (1-tailed)

Table 6 Bivariate one-tailed Pearson correlation study of various groundwater quality metrics (2019)

Parameters	pH	EC	TH	TDS	Co3	HCO3	Cl	SO4	NO3	Ca	Mg	Na	K	Fe
pH	1	-	-	-	-	-	-	-	-	-	-	-	-	-
EC	-0.052	1	-	-	-	-	-	-	-	-	-	-	-	-
TH	.497**	.431*	1	-	-	-	-	-	-	-	-	-	-	-
TDS	-0.121	.881**	.483**	1	-	-	-	-	-	-	-	-	-	-
CO ₃ ⁻	0.069	-0.107	0.31	-0.1	1	-	-	-	-	-	-	-	-	-
HCO ₃ ⁻	0.243	-0.334	-0.033	-.442*	0.216	1	-	-	-	-	-	-	-	-
Cl ⁻	0.123	.339*	.451*	.434*	-0.103	-0.233	1	-	-	-	-	-	-	-
SO ₄ ²⁻	0.267	0.103	.413*	0.088	0.179	0.028	0.052	1	-	-	-	-	-	-
NO ₃ ⁻	-.466**	0.066	0.022	0.08	0.25	-0.245	0.119	0.216	1	-	-	-	-	-
Ca ²⁺	.350*	.460*	.942**	.515**	0.287	-0.169	.489**	.477**	0.135	1	-	-	-	-
Mg ²⁺	.551**	0.07	.489**	0.081	0.166	0.315	0.074	-0.01	-0.276	0.172	1	-	-	-
Na ⁺	-.379*	.521**	0.188	.603**	-0.011	-0.157	.370*	0.095	.433*	0.234	-0.051	1	-	-
K ⁺	0.044	.517**	.369*	.538**	-0.2	-0.086	.454*	-0.028	0.125	0.323	0.242	.819**	1	-
Fe ²⁺	-0.279	-0.012	-.466**	-0.2	-0.099	-0.202	-0.159	-0.242	0.092	-.366*	-.412*	-0.264	-.399*	1

* At the 0.05 level, the correlation is significant (1-tailed)

** At the 0.01 level, the correlation is significant (1-tailed)

Table 7 Groundwater quality parameter coefficients of determination (2011)

Parameters	R – value	Coefficient of determination (R ²)	Shared variance
EC—pH	0.325	0.105	10.5
TDS- pH	0.325	0.105	10.5
CO ₃ ⁻ —pH	0.106	0.011	1.1
HCO ₃ ⁻ —pH	0.297	0.088	8.8
Cl ⁻ —HCO ₃ ⁻	0.088	0.004	0.4
SO ₄ ²⁻ —pH	0.246	0.061	6.1
NO ₃ ⁻ —CO ₃ ⁻	-0.15	0.022	2.2
Ca ²⁺ - NO ₃ ⁻	0.223	0.049	4.9
Mg ²⁺ —pH	0.133	0.017	1.7
Na ⁺ —pH	0.226	0.051	5.1
K ⁺ - pH	0.246	0.061	6.1
Fe ²⁺ —SO ₄ ²⁻	0.184	0.033	3.3

as pH, EC, TH, TDS, HCO₃⁻, CO₃⁻, Cl⁻, NO₃⁻, SO₄²⁻, Ca²⁺, Mg²⁺, Na⁺, K⁺ and Fe²⁺, is based on BIS (2012) and WHO recommendations (2006). Using GIS, generate spatial distribution maps based on water quality parameters.

Hydrogen ion (pH) and electrical conductivity

The hydrogen ion is used to evaluate the acidity or alkalinity of a solution (pH). It is a measure of hydrogen ion

Table 8 Groundwater quality parameter coefficients of determination (2019)

Parameters	R – value	Coefficient of determination (R ²)	Shared variance
EC – pH	-0.052	0.002	0.2
TDS- pH	-0.121	0.014	1.4
CO ₃ ⁻ —TH	0.31	0.096	9.6
HCO ₃ ⁻ —pH	0.069	0.004	0.4
Cl ⁻ —HCO ₃ ⁻	0.233	0.054	5.4
SO ₄ ²⁻ —pH	0.267	0.071	7.1
NO ₃ ⁻ —CO ₃ ⁻	0.25	0.062	6.2
Ca ²⁺ - CO ₃ ⁻	0.135	0.018	1.8
Mg ²⁺ —pH	0.151	0.022	2.2
Na ⁺ —SO ₄ ²⁻	0.379	0.143	14.3
K ⁺ —pH	0.044	0.001	0.1
Fe ²⁺ —NO ₃ ⁻	0.242	0.058	5.8

concentration, or more precisely, hydrogen ion activity. The significance of the 2011 pH ranged from 3.0 to 8.3 and 3.7 to 7.3 in 2019. Table 1 demonstrates that the BIS and WHO suggest a pH range of 7.0 to 8.5 for drinking water. At low pH levels, water becomes corrosive, causing organoleptic issues. The acidic water promotes corrosion in well service construction components such as casings and screens, as well as domestic items. The spatial distribution of pH in the investigation was calculated between 2011 and 2019 using the Interpolated Distance Weighted (IDW) maps illustrated in Fig. 8a and b. All of the water samples were confirmed to be within permissible limits. In 2011, the majority of the samples were alkaline, although within permissible limits. In addition, an acidic pH was found in a slight of the study area. In 2019, the majority of water samples will be performed as much as possible. The pH values increase as far in the northern region of the area of study. The results suggest that the pH of the study area is not affected by the various industries in the Kannur area.

In electrical conductivity (EC), most of the water samples (25) of 2011 ranging from 31 to 505 µScm, and in 2019 the range were observed to be 35 to 236 µScm respectively. The capacity of a solution to lead an electrical flow is administered by the movement of the arrangements and is subject to the nature and quantities of the ionic species in that arrangement. The significance of EC stems from its salinity measurement, which impacts the taste of water and, as a result, the user's acceptance of it. When comparing 2011 and 2019, the value of EC fluctuates greatly in 2019, as shown in Fig. 9a and b. A few areas in the northeast have been discovered that are not permitted by WHO standards. The highest conductivity value may be attributed to the highest concentration of ionic components.

Total hardness and total dissolved solids

Total hardness is crucial, when it comes to water for domestic use. In 2011, total hardness levels ranged from 15.15 to 18.18 mg/l, whereas in 2019, total hardness levels varied from 14 to 188 mg/l. Hardness is a quality of water that prevents foam formation with cleaners and increases the water's limits. The amount of dissolved calcium and magnesium in the water affects its hardness. It is commonly represented by a set of CaCO₃ equivalents (WHO, 2006). By comparing 2011

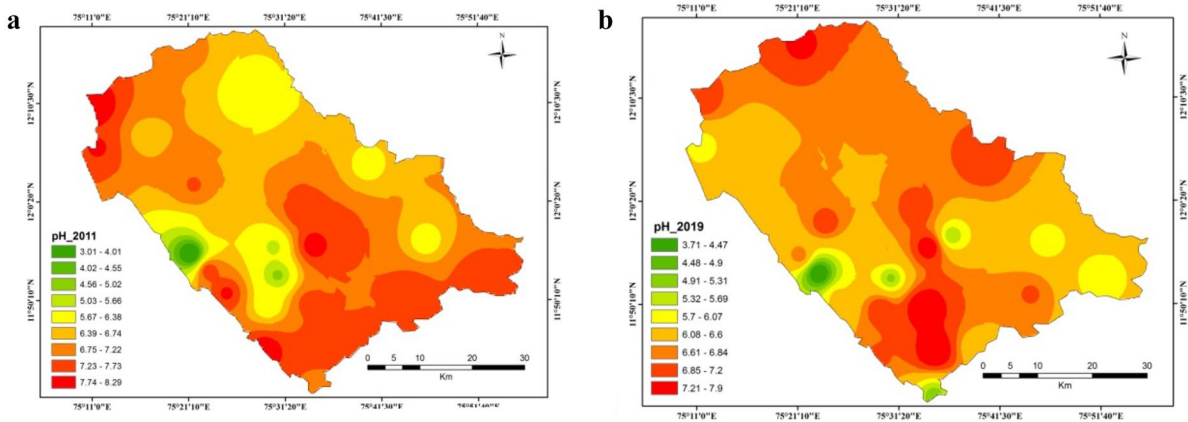


Fig. 8 a, b Spatial distribution comparison map of pH in 2011 and 2019

and 2019, in certain places, water turns too hard due to several industries located in the study area. Groundwater samples clearly show the significant influence of wastes and effluents from various industries. It has been suggested that it contributes to the creation of kidney stones and causes heart issues. As illustrated in Fig. 10a and b, industries have a negative impact on ground water supplies. In general, hardness is a mix of calcium and magnesium ions. As a result, rainfall may eventually result in increased in water hardness as calcium and magnesium-containing minerals dissolve.

The TDS levels in groundwater samples were observed in the range of 21.6 to 177.6 mg/l in 2011 and 22 to 268 mg/l in 2019. The high TDS values are caused by salts eroding from the surrounding soil, affecting water

quality and maybe causing gastrointestinal disturbances in humans (WHO, 2006). During the rainy season in Kannur, the maximum guideline requirement of 500 mg/L was exceeded. The main contributors to high TDS values include groundwater activity in rocks, untreated sewage, waste deposits, and agrochemicals. The presence of high TDS levels in water causes a change in the flavour of non-potable water. As illustrated in Fig. 11a and b, the regional variance in TDS values illustrates the effect of industrialization.

Carbonate and bicarbonate

In 2011, carbonate ranged from 0 to 11.61 mg/l and in 2019 from 0.1 to 5.32 mg/l. Figure 12a and b shows that

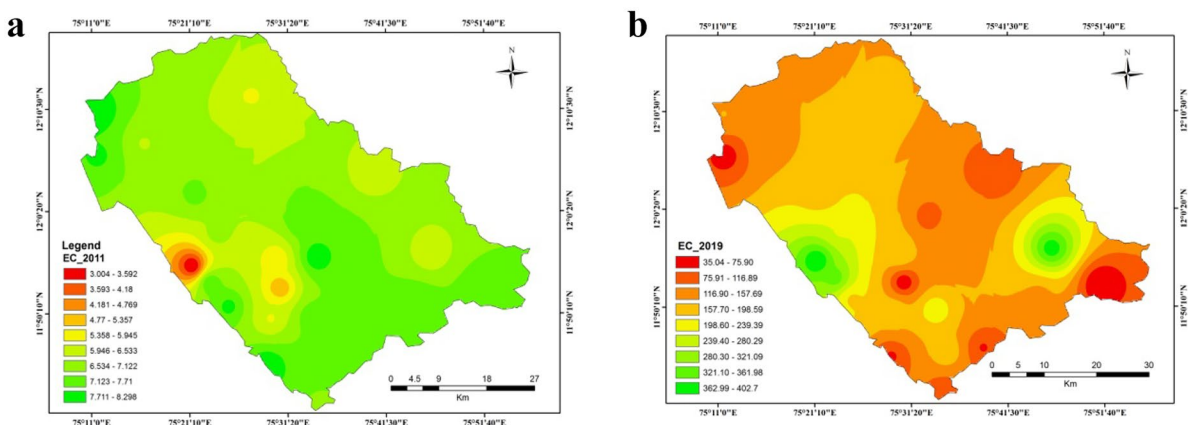


Fig. 9 a, b Spatial distribution comparison map of EC in 2011 and 2019

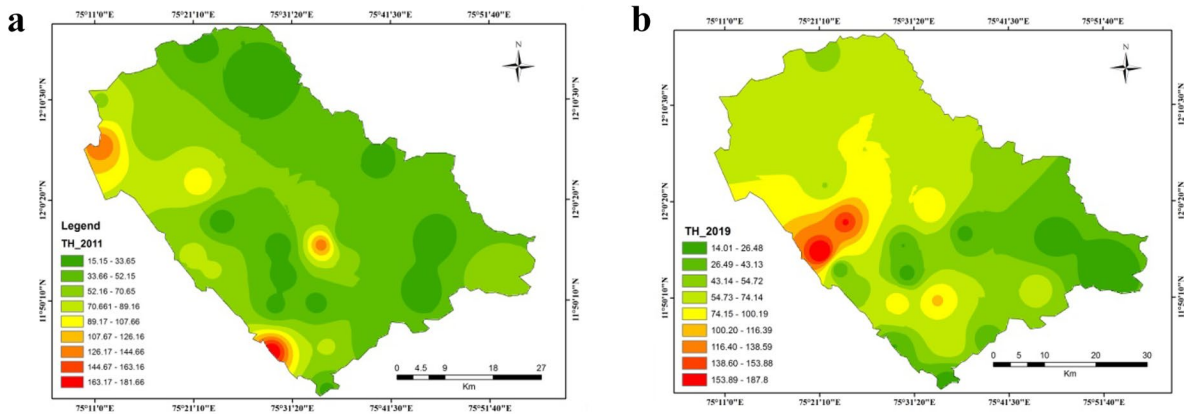


Fig. 10 a, b Spatial distribution comparison map of TH in 2011 and 2019

the northeast and southwest regions were observed to have high values in 2011 and 2019. A few of the areas exceed the limit in both the BIS and WHO standards. As a result, groundwater is used for water system purposes, but dissipation causes an increase in ion concentration in the underground. In 2011, bicarbonate concentrations ranged from 0 to 175.74 mg/l, and in 2019, it was from 10.69 to 213.2 mg/l while comparing the entire areas that were observed within the permissible limit. The outcome map (Fig. 13a, b) shows that the northeast, southwest, and little space in the focal piece of the investigation territory have moderate levels. When the groundwater used for water system purposes evaporates, it naturally influences the underground with an increment in the concentration of ions. Further dispersion from the irrigated zone causes a high concentration of salts, which is especially visible in carbonates in soils.

Chloride and sulphate

Cl⁻ concentrations ranged from 5.75 to 59.46 mg/l in 2011 and 0 to 25.52 mg/l in 2019. The southeast part of the region has high fixations in 2011, and the southeast and southwest areas were observed in high concentrations, as shown in Fig. 14a and b. Cl⁻-bearing rocks such as sodalite chloroapatite, which are tiny portions of igneous and metamorphic formations and generate little of the total volume of aquifers, may be to blame for the elevated Cl. Cl⁻-bearing rocks like sodalite and chloroapatite, which are minor components of igneous and metamorphic rocks that generate even less than the total underground water quantity, could be to blame for the high Cl. Chloride levels that are undeniably high can be dangerous for your health, affecting the heart and kidneys, as well as taste, acid reflux,

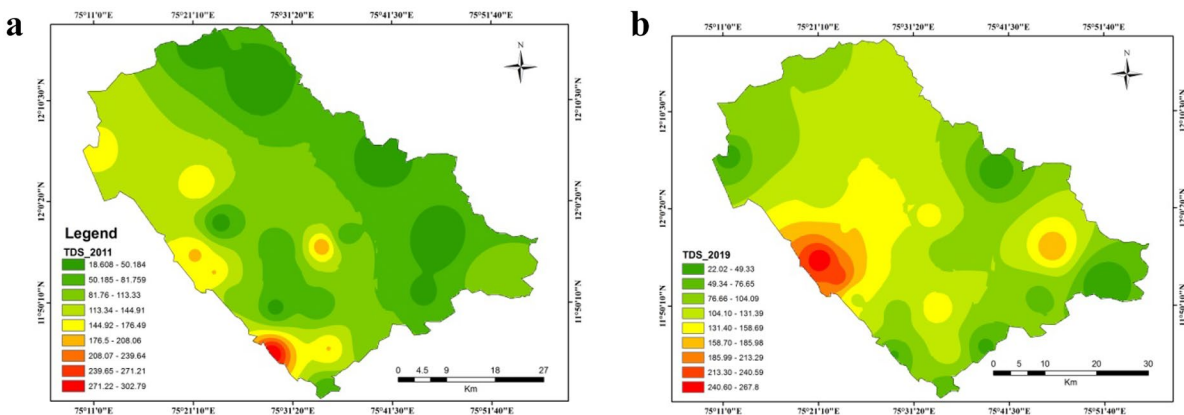


Fig. 11 a, b Spatial distribution comparison map of TDS in 2011 and 2019

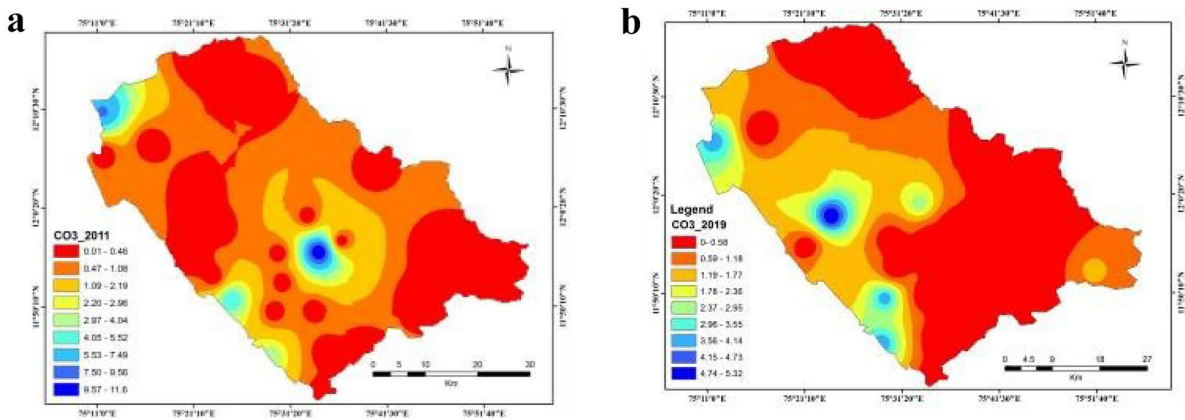


Fig. 12 a, b Spatial distribution comparison map of CO₃- (2011 and 2019)

erosion, and satisfaction. Sulphate fixations range from 0 to 30.6 mg/l in 2011 and in 2019, 0 to 100 mg/l as presented in Fig. 15a and b. It shows that the majority of the samples (southeast) fall within the permissible limit and a few zones fall under permissible levels.

Calcium and magnesium

Calcium concentrations range from 1.62 to 47.62 mg/l in 2011, and 4 to 160 mg/l in 2019. The difference in calcium ion concentration between 2011 and 2019 shows that the southeast portion of the study region has high concentrations by WHO criteria. The human body develops kidney or bladder stones as a result of elevated calcium concentrations. In common, about 12% of the sampling locations indicated calcium content values higher

than the standard. In any of the surface water samples, however, there is no additional calcium. Figure 16a and b shows the IDW calcium maps from 2011 to 2019.

Magnesium concentrations range from (2011) 0 to 15.22 mg/l and (2019) 4 to 62 mg/l respectively. The maximum of the samples in 2011 and 2019 was under the permissible limit of the WHO and BIS standards. A few areas were observed to be exceeding the limit. As shown in Fig. 17a and b, the southwest and northwest regions of the region have high concentrations. A high Mg²⁺ content in animals promotes scouring disorders.

Sodium and potassium

In 2011, Na⁺ values varied from 2.8 to 28.5 mg/l, while in 2019, they ranged from 0.6 to 5.4 mg/l. Figure 18a

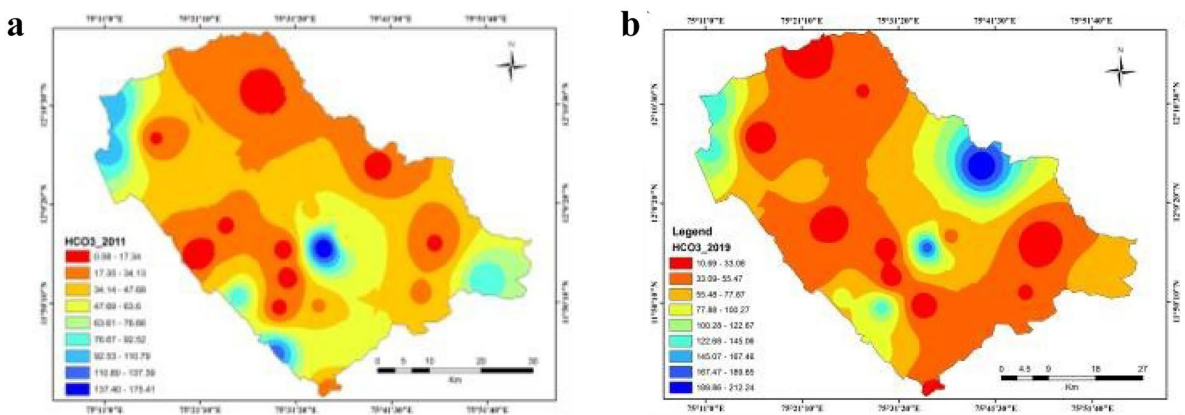


Fig. 13 a, b Spatial distribution comparison of HCO₃- (2011 and 2019)

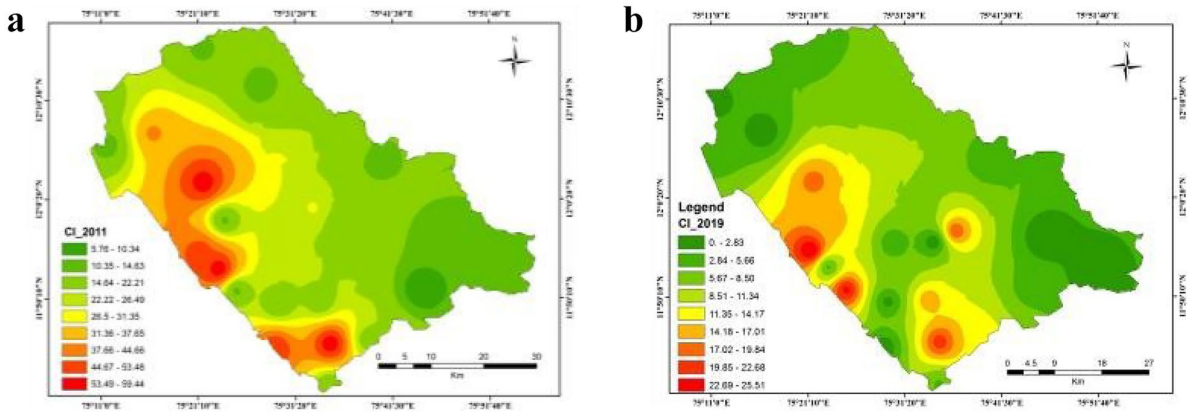


Fig. 14 a, b Spatial distribution comparison map of Cl in 2011 and 2019

and b illustrates that levels are high in the northeast and southeast. According to WHO guidelines, the majority of the samples are within the permissible limits, but a small fraction of those slightly exceed them. High Na^+ levels are harmful because they can cause difficulties with the heart, kidneys, and circulation.

Potassium concentrations ranged from 0.1 to 9.6 mg/l in 2011 and 0 to 1.2 mg/l in 2019 of the samples were found to be within BIS and WHO acceptable levels. As shown in Fig. 19a and b, very few samples are obtained that are not permissible, and the southwest and northeast parts of the study region have moderate levels.

Nitrate and iron

Nitrate concentrations range from 0 to 3.47 mg/l in 2011 and 0.001 to 2 mg/l in 2019. Nitrate concentration varies in 2011 and 2019. Figure 20a and b shows that the northwest and southwest parts of the study area have concentrations according to BIS and WHO standards. Figure 21a and b indicates that iron concentrations range from 0 to 3.79 mg/l in 2011 and from 0 to 4.65 mg/l in 2019. According to WHO guidelines, the majority of samples facing northwest and southwest parts are allowed to reach the permissible limit,

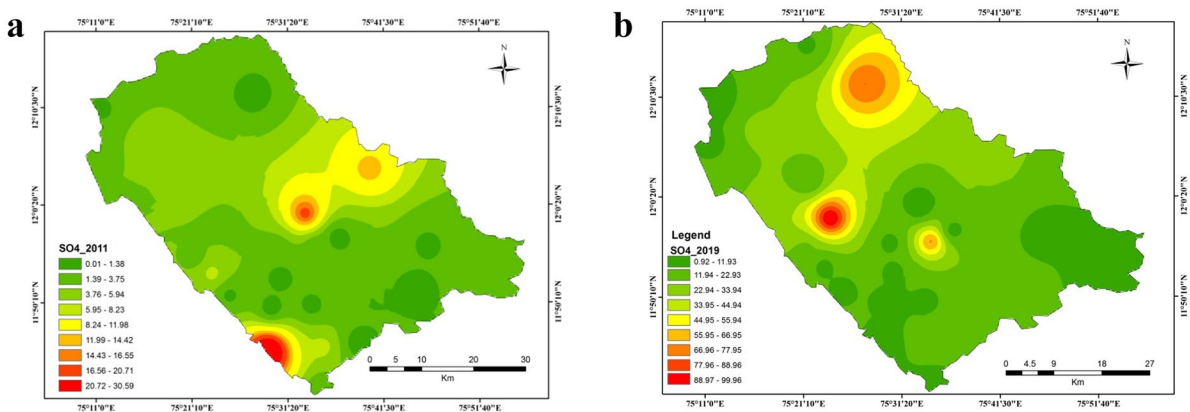


Fig. 15 a, b Spatial distribution comparison map of SO4 in 2011 and 2019

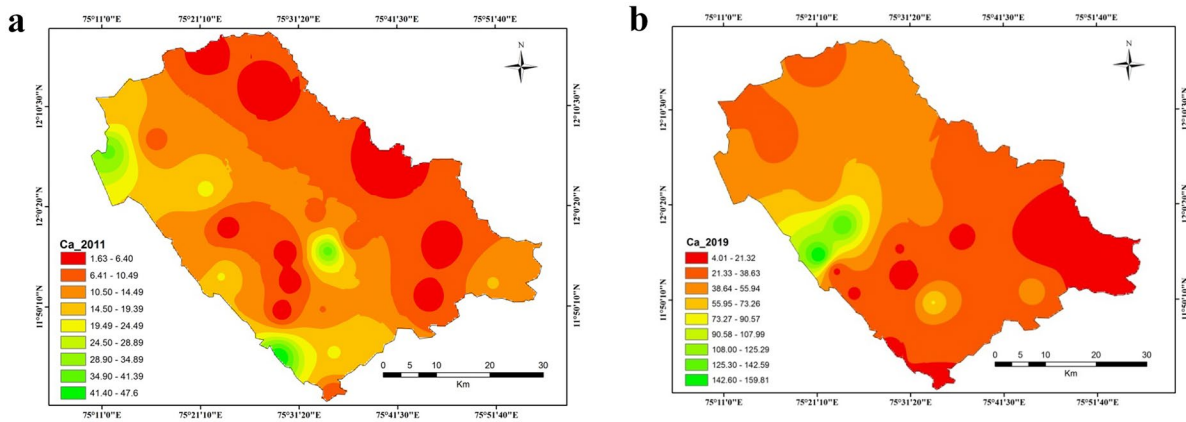


Fig. 16 a, b Spatial distribution comparison map of Ca in 2011 and 2019

while less than half of samples facing northeast parts are covered in a few areas that do not exceed the limits.

Water quality index

The total status of groundwater quality for drinking purposes is shown by the water quality index. The study areas can be categorised as excellent, good, moderate, or poor based on water quality index (WQI) levels. The good areas of Vayakkara, Alakkode, Vayathur, Aralam, Vekkalam, Peringathur, Koothuparamba, Eruvatty, Ancharakkandy, Koodali, and Kalliassery were recognised by WQI in 2011. The water conditions in

the Cheruthazam, Irikkur, Chavassery, Kolavellur, Edakkad, and Kottiyoor areas were excellent. Water quality was moderate in Panoor, Kannur, Chirakkal, Thaliparamba, Payyannur, and Karivellur locations. Figure 22 shows the relatively poor water quality at Mattannur and Thalassery.

According to WQI, Alakkode, Vayathur, Vekkalam, Edakkad, Panoor, Irikkur, Thaliparamba, and Karivellur were among the top-rated locations in 2019. Water sources of high quality include Vayakkara, Cheruthazham, Payyannur, Koodali, Ancharakkandy, Peringathoor, Kolavellur, Vekkalam, Chavassery, and Kottiyoor. Figure 23 illustrates that while the ground water

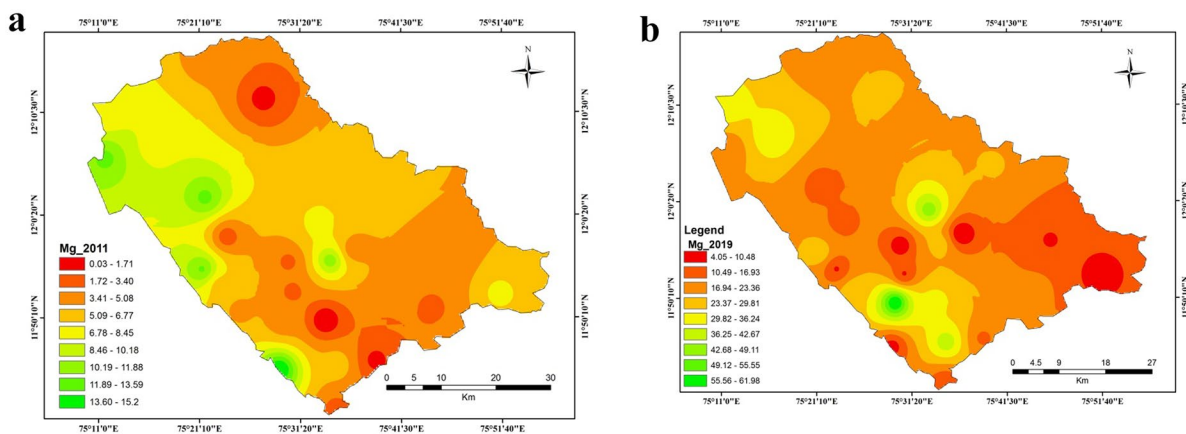


Fig. 17 a, b Spatial distribution comparison map of Mg in 2011 and 2019

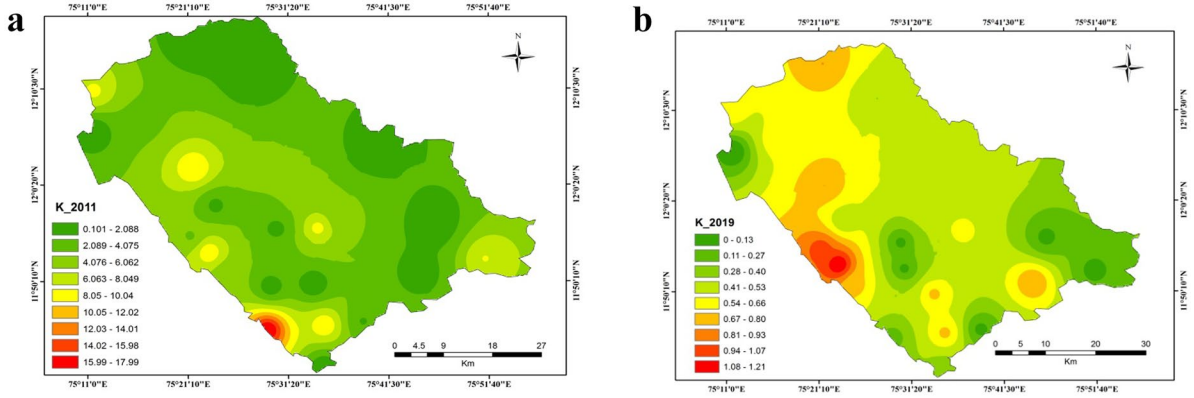


Fig. 18 a, b Spatial distribution comparison map of Na in 2011 and 2019

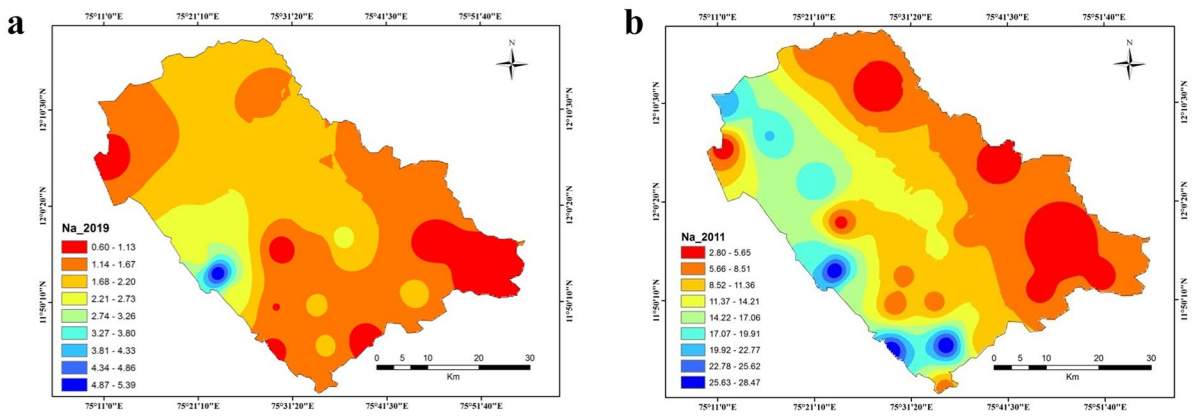


Fig. 19 a, b Spatial distribution comparison map of K in 2011 and 2019

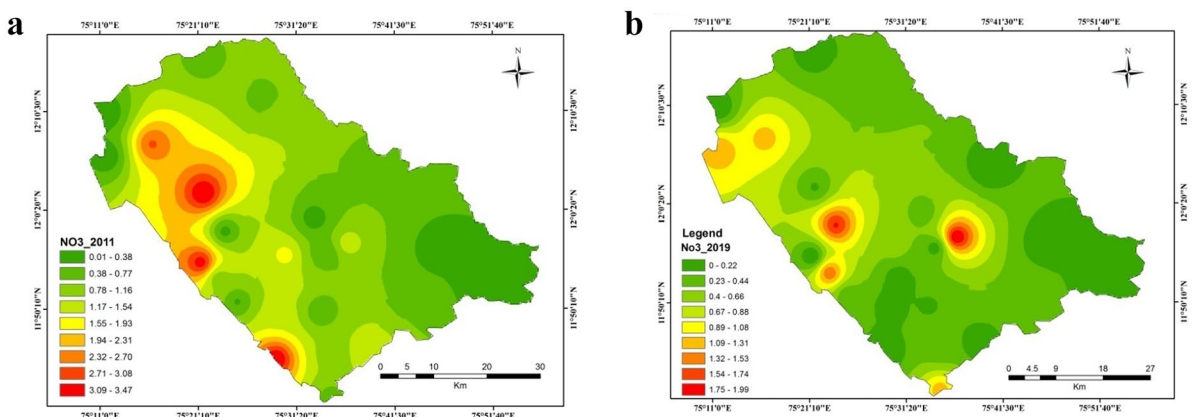


Fig. 20 a, b Spatial distribution comparison map of NO3 in 2011 and 2019

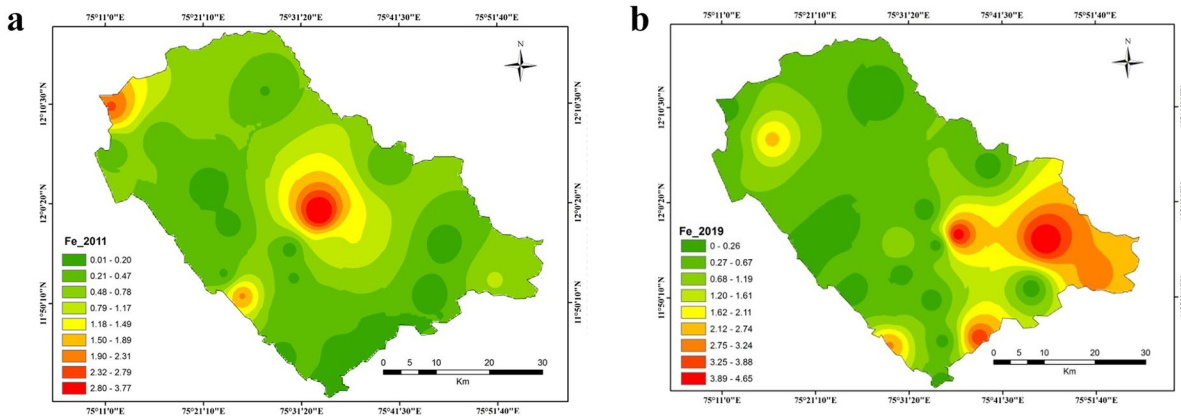


Fig. 21 a, b Spatial distribution comparison map of Fe in 2011 and 2019

quality in the Chirakkal, Kalliassery, and Thalassery areas was discovered to be bad, it was present in the Kannur, Koothuparamba, Eruvatti, and Aralam areas in a moderate range. When comparing the WQI of the ground water samples from 2011 and 2019, more areas are found to be of poor quality, while other areas go from exceptional to good to moderate range. The Thalassery region was noted to be more WQI in both 2011 and 2019.

The lower WQI in the study’s overall findings denotes the high quality of the groundwater. Based on the results from 2011, it can be assumed that most of the sampling

sites in the study area had acceptable water quality, with the exception of Mattannur and Thalassery, with a WQI value of 0 to 25. The majority of the sampling locations in the study area fall within the 0 to 25 range, which indicates excellent water quality, according to the results obtained. However, numerous groundwater quality indices that had previously shown high water quality have changed when compared to 2011. In the Chirakkal region, one indicator of low water quality is displayed. According to the WQI value obtained for the various samples in 2019, most of the area around industrial sites in the Kannur district’s water is safe for human consumption.

Fig. 22 The study area’s water quality index map (2011)

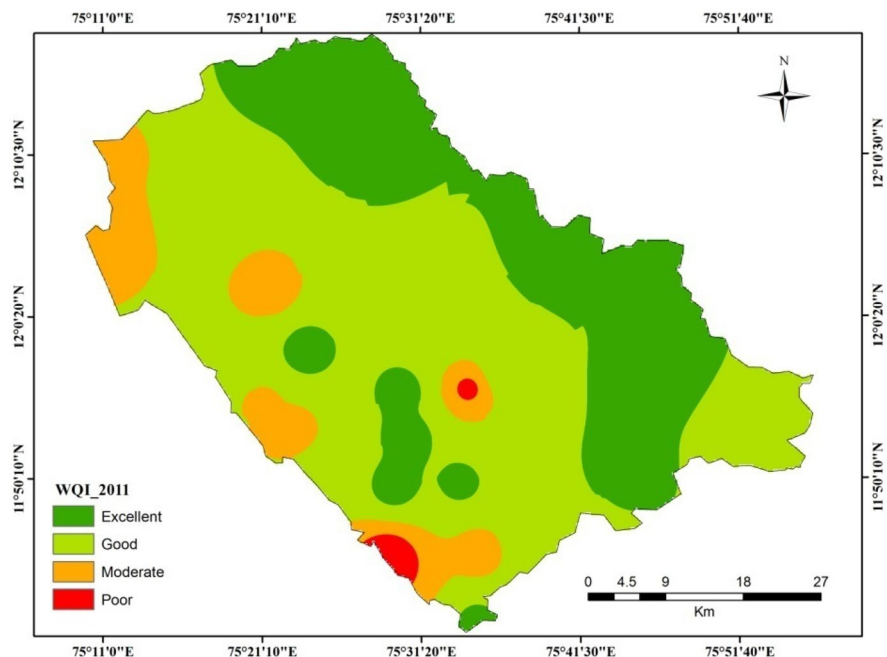
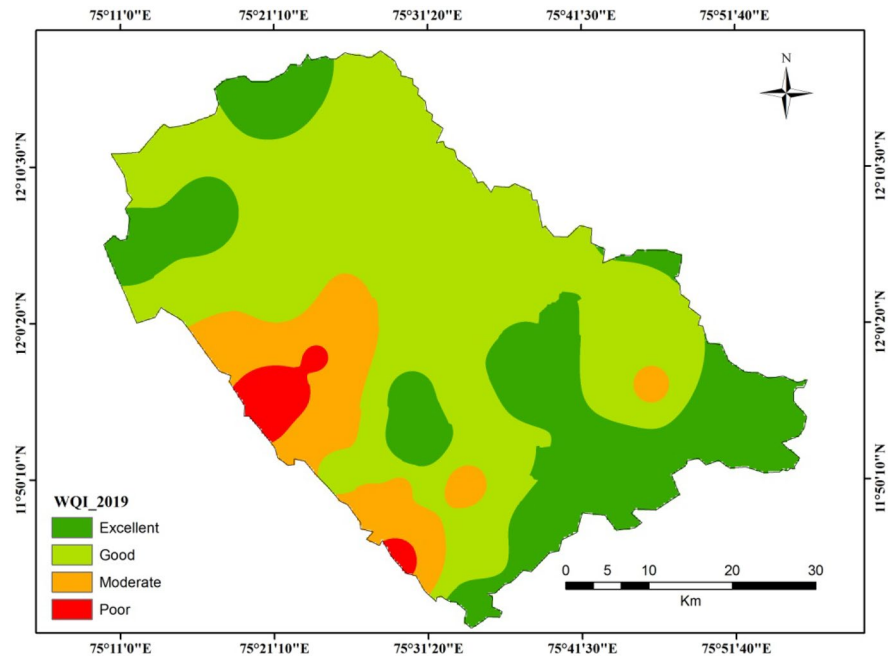


Fig. 23 The study area's water quality index map (2019)



The WQI's overall results were evaluated well. For this study, groundwater quality in the northern regions is usually excellent. Overall, the 2011 and 2019 analyses reveal that the western part of the district has poor potable water quality. The higher values of iron, nitrate, total dissolved solids, hardness, sodium, potassium, calcium, magnesium, bicarbonate, chloride, and pH at this location have been discovered to be the main causes of the high WQI value. The overall results of the WQI were observed to be in good condition. Most of the regions in the northern part of the district have good water quality. The study illustrates (in 2011 and 2019) that the western part of the district shows poor potable water quality. The overall quality of groundwater is excellent in the entire study area.

Conclusion

The study of 25 groundwater samples taken from various portions of rural and industrial areas of Kannur district. It was studied that various physico-chemical analyses completed in the study area. The spatial distribution of several groundwater quality indicators was communicated using statistical and GIS innovations in an effort to evaluate the nature of groundwater.

Additionally, the groundwater quality of the years 2011 and 2019 was compared. Most of the groundwater samples in the study region are below the allowed level. In some instances, there are exceptions. According to the overlay of thematic maps for essential aspects, a wider part of the district in the study region has portable groundwater.

In PCA, four factors from the 2011 dataset were recovered with eigen values greater than unity, while four factors from the 2019 dataset were retained with eigen values greater than unity, accounting for 73.4 percent of the total variance of the data set. The data sets' extreme values are sensitive to HCA. The loading of the factor on the factor reveals natural pollution and soil erosion phenomena carried on by drifting fluctuations. The major instructive latent components for each season were extracted using PCA. The results of groundwater valuable studies can be improved by using the Pearson connection coefficients as a multivariate statistical tool to help identify measurably relevant features of information variance. All of the data were analysed using a Pearson correlation matrix. The purpose of the groundwater samples is to identify any statistical relationships between various pairs of ground water quality indicators. As observed in the comparison between 2011 and 2019, several locations

have declined in value from 2011 and it cause of the poor industrialization.

This study reveals that almost all the samples collected and tested from Kannur district are portable, but there are some samples that show some variation in some of the properties from the permissible limit in BIS and WHO standards. The water quality index, as calculated, provides useful information by classifying specific places as excellent, good, poor, or unsuitable for drinking. WQI and GIS assist in the provision of more valuable data for water quality evaluation and problem solving. The study area is under threat due to some critical issues of environmental pollution. It is concluded that all the samples will be portable if proper remedial measures are put into practice. It is to assess the groundwater quality in Kannur district from a GIS perspective, and to create a geo-referenced groundwater database and maps that may be used to establish sustainable groundwater use strategies. Both governmental and non-governmental organisations have attempted to use GIS to locate the problem areas. The study was providing more useful information to the organisers and chiefs in order to develop strategy rules for effective management of groundwater assets.

Data availability In 2011, 25 samples were obtained from the investigation zone in secondary data at Centre for Water Resources Department and Management (CWRDM), Kozhikode. For 2019, 25 groundwater field samples were collected and completed with physicochemical analysis in the laboratory.

Declarations

Conflict of interest The authors declare no competing interests.

References

Abbulu, Y., & Rao, G. V. R. S. (2013). A Study on physico-chemical characteristics of groundwater in the industrial zone of Visakhapatnam, Andhra Pradesh. *American Journal of Engineering Research (AJER)*, 2(10), 112–116.

Abinandan, S., Anand, B. A., & Subramaniam, S. (2014). Assessment of physico-chemical characteristics of groundwater: A case study. *International Journal of Environmental Health Engineering*, 2(6), 34–37.

Alam W, Gyanendra Y, Chanda R, Laishram RJ, Nesa N (2020a) Hydrogeochemical assessment and evaluation of groundwater quality in selected areas of Bishnupur district, Manipur. *Journal of the Geological Society of India*, 96(3):272–278.

APHA. (2005). *Standard methods for the examination of water and waste water* (21st ed.). American Public Health Association.

Arulbalaji, P., & Gurugnanam, B. (2017). Groundwater quality assessment using geospatial and statistical tools in Salem District, Tamil Nadu, India. *Applied Water Science*, 7, 2737–2751. <https://doi.org/10.1007/s13201-016-6120501-5>

Arumugam, K., & Elangovan, K. (2009). Hydrochemical characteristics and groundwater quality assessment in Tirupur Region, Coimbatore District, Tamil Nadu, India. *Environmental Geology*, 58, 1509. <https://doi.org/10.1007/s00254-008-1652-y>

Balakrishnan, P., Saleem, A., & Mallikarjun, N. D. (2011). Groundwater quality mapping using geographic information system (GIS): A case study of Gulbarga city, Karnataka, India. *African Journal of Environmental Science and Technology*, 5(12), 1069–1084.

Balamurugan, P., Kumar, P. S., Shankar, K., Sajil, Kumar P. J. (2020). Impact of climate and anthropogenic activities on groundwater quality for domestic and irrigation purposes in Attur region, Tamilnadu, India Desal. *Water Treat*, 208, 172–195. <https://doi.org/10.5004/dwt.2020.26452>.

Bhasin, S. K., Singh, A., & Kaushal, J. (2008). Statistical analysis of water falling into western Yamuna canal from Yamuna nagar industrial belt and its effect on agriculture. *Journal of Environmental Research and Development*, 2(3), 393–401.

BIS (Bureau of Indian Standards) 10500. (2012). *Indian Standard-drinking water specification*. Manak Bhavan, New Delhi. 1–16.

Central Ground Water Board (CGWB) (2007). Manual on artificial recharge of groundwater. Ministry of water resources, government of India.

Chandrasekar, T., Keesari, T., Gopalakrishnan, G., Karuppannan, S., Senapathi, V., Sabarathinam, C., & Viswanathan, P. M. (2021). Occurrence of heavy metals in groundwater along the lithological interface of K/T boundary, Peninsular India: A special focus on source, geochemical mobility and health risk. *Archives of Environmental Contamination and Toxicology*, 80, 183–207.

Chaurasia, A. K., Pandey, H. K., Tiwari, S. K., et al. (2018). Groundwater quality assessment using water quality index 629 (WQI) in parts of Varanasi District, Uttar Pradesh, India. *Journal of Geological Society of India*, 92(76–82), 630. <https://doi.org/10.1007/s12594-018-0955-1>

Courault, D., & Monestiez, P. (1999). Spatial interpolation of air temperature according to atmospheric circulation patterns in southeast France. *International Journal of Climatology*, 19, 365–378.

Davis. (2002). *Statistical methods for the analysis of repeated measurements*. Berlin: Springer.

Emenike, P. C., Nnaji, C., & Tenebe, I. T. (2018). Assessment of geospatial and hydrochemical interactions of groundwater quality, southwestern Nigeria. *Environment Monitoring Assessment*, 190, 440. <https://doi.org/10.1007/s10661-018-6799-8>

Farnham, M., Johannesson, K. H., Singh, A. K., Hodge, V. F., Stetzenbach, K. J. (2003) Factor analytical approaches for evaluating groundwater trace element chemistry data. *Analytical Chimica Acta*, 490, 123–138.

Gajbhiye S, Singh SK, Sharma SK (2015) Assessing the effects of different land use on water quality using multi-temporal landsat data. In: Siddiqui AR, Singh PK (eds) Resource management and development strategies: a geographical perspective. Pravalika Publication, Allahabad, pp 337–348. ISBN: 91 8-93-84292-21-8.

- Gorai, A. K., & Kumar, S. (2013). Spatial distribution analysis of groundwater quality index using GIS: A case study of Ranchi Municipal Corporation (RMC) Area. *Geoinformatics and Geostatistics: An Overview*, 1(2), 1–11.
- Gou X, Li Y, G. Wang (2007) Heavy metal concentrations and correlations in rain-fed farm soils of Sifangwu Village, Central Gansu Province, China. *Land Degradation and Development*, 18(1), 77–88.
- Halim, M. A., Majumder, R. K., Nessa, S. A., Oda, K., Hiroshiro, Y., et al. (2010). Arsenic in shallow aquifer in the eastern region of Bangladesh: Insights from principal component analysis of groundwater compositions. *Environmental Monitoring Assessment*, 61, 453–472.
- Han, Y. M., Du, P. X., Cao, J. J., & Posmentier, E. S. (2006). Multivariate analysis of heavy metal contamination in urban dusts of Xi'an, Central China. *Science of The Total Environment*, 355, 176–186.
- Islam, B. (2013). Legal aspects of remote sensing. *International Journal for Legal Development and Allied Issues*, 1(30), 50.
- Islam, A. R. M. T., Rakib, M. A., Islam, M. S., Jahan, K., & Patwary, M. A. (2015). Assessment of health hazard of metal concentration in groundwater of Bangladesh. *American Chemical Science Journal*, 5(1), 41–49. <https://doi.org/10.9734/ACSj/2015/13175>
- Jeihouni, M., Toomanian, A., Shahabi, M., & Alavipanah, S. K. (2014). Groundwater quality assessment for drinking purpose using GIS modelling (case study :City of tabriz). *The International Archives of Photogrammetry Remote Sensing and Spatial Information Sciences*, 40(2), 163.
- Karunanidhi, D., Aravinthasamy, P., Deepali, M., Subramani, T., & Shankar, K. (2021). Groundwater pollution and human health risks in an industrialized region of Southern India: Impacts of the COVID-19 lockdown and the monsoon seasonal cycles. *Archives of Environmental Contamination and Toxicology*, 80, 259–276.
- Khodapanah, L., Sulaiman, W., & Khodapanah, N. (2009). Groundwater quality assessment for different purposes in Eshtehard District, Tehran, Iran. *European Journal of Scientific Research*, 36, 543–555.
- Kumar, A. R., & Riyazuddin, P. (2008). Application of chemometric techniques in the assessment of groundwater pollution in a suburban area of Chennai city, India. *Current Science*, 94(8), 1012–1022.
- Liu, Z., & Yang, H. (2018). The impacts of spatiotemporal landscape changes on water quality in Shenzhen, China. *International Journal of Environmental Research and Public Health*, 15, 1038.
- MacDonald, A., Bonsor, H., Ahmed, K., et al. (2016). Groundwater quality and depletion in the Indo-Gangetic Basin mapped from in situ observations. *Nature Geosciences*, 9, 762–766. <https://doi.org/10.1038/ngeo2791>
- Magesh, N. S., & Chandrasekhar, N. (2012a). Evaluation of spatial variation in groundwater quality by water quality index and GIS technique a case study of Virudunagar District, Tamil Nadu, India. *Arabian Journal of Geosciences*, 6(16), 1883–1898.
- Magesh, N. S., Prasanth, S. S., Jitheshlal, K. V., Chandrasekar, N., & Gangadhar, K. (2012b). Evaluation of groundwater quality and its activity for drinking and agricultural use in the coastal stretch of Alappuzha district, Kerala, India. *Applied Water Science*, 2(3), 165–175.
- Masoud, A. A. (2014). Groundwater quality assessment of shallow aquifers west of the Nile Delta (Egypt) using multivariate statistical and geostatistical technique. *Journal of African Earth Science*, 95, 123–137.
- McKenna, J. E., Jr. (2003). An enhanced cluster analysis program with bootstrap significance testing for ecological community analysis. *Environmental Modelling Software*, 18(3), 205–220.
- Mendiguchía, C., Moreno, C., Galindo, R. M. D., & García-Vargas-Vargas, M. (2004). Using chemometric tools to assess anthropogenic effects in river water. A case study: Guadalquivir River (Spain). *Analytica Chimica Acta*, 515, 143–149.
- Mitas, L., & Mitasova, H. (1999). Spatial interpolation. In P. Longley, M. F. Goodchild, D. Maguire & D. Rhind (Eds.), *Geographical Information Systems* (2nd ed. Vol. 1, pp. 481–492). Principles and Technical Issues.
- Molla, M. A., Saha, N., Salam, S. A., & Rakib-uz-Zaman, M. (2015). Surface and groundwater quality assessment based on multivariate statistical techniques in the vicinity of Mohanpur, Bangladesh. *International Journal of Environmental Health Engineering*, 4, 18. <https://doi.org/10.4103/2277-9183.157717>
- Nagaraju, A., Thejaswi, A., & Sreedhar, Y. (2016). Assessment of Groundwater Quality of Udayagiri area, Nellore District, Andhra Pradesh, South India Using Multivariate Statistical Techniques. *Earth Sciences Research Journal*, 20, E1–E7.
- Nawab J, Khan S, Aamir M, Shamshad I, Qamar Z, Din I, Huang Q (2016) Organic amendments impact the availability of heavy metal (loid) s in mine-impacted soil and their phytoremediation by *Penisetum americanum* and *Sorghum bicolor*. *Environmental Science and Pollution Research*, 23(3), 2381–2390. <https://doi.org/10.1007/s11356-015-5458-7>.
- Padmanabha Iyer, C. S., Sindhu, M., Kulkarni, S., Tambe, S., et al. (2003). Statistical analysis of the physico-chemical data on the coastal waters of Cochin. *Journal of Environmental Monitoring*, 5, 324–327.
- Pallant, J. (2011). *A step by step guide to data analysis using the SPSS Program: Survival manual* (4th ed.). McGraw-Hill.
- Pandian, M., & Jayachandran, N. (2014). Groundwater quality mapping using remote sensing and GIS a case study of Thuraiyur and block Tiruchirappalli district, Tamil Nadu, India. *International Journal of Advanced Remote Sensing and GIS*, 3(1), 580–591.
- Patil, V. T., & Patil, P. R. (2010). Suitability assessment of groundwater for irrigation and drinking purpose in the northern region of Jordan. *Journal of Environmental Science and Technology*, 5, 274–290.
- Rahman, M. S., & Gagnon, G. A. (2014). Bench-scale evaluation of drinking water treatment parameters on iron particles and water quality. *Water Research*, 48, 137–147.
- Rahman, M. A. T. M. T., Rahman, S. H., & Majumder, R. K. (2012). Groundwater quality for irrigation of deep aquifer in southwestern zone of Bangladesh. *Songklanakarin Journal of Science and Technology*, 34(3), 345–352.

- Rahman, M. A. T. M. T., Saadat, A. H. M., Islam, M. S., Al-Mansur, M. A., & Ahmed, S. (2014). Groundwater characterization and selection of suitable water type for irrigation in the western region of Bangladesh. *Applied Water Science*, 7, 233–243. <https://doi.org/10.1007/s13201-014-0239-x>
- Rani, A., & Babu, D. S. S. (2008). A statistical evaluation of ground water chemistry from the west coast of Tamil Nadu, India. *Indian Journal of Marine Sciences*, 37(2), 186–192.
- Reza, R., & Singh, G. (2010). Application of water quality index for assessment of pond water quality status in Orissa, India. *Current World Environment*, 5(2), 305–310. <https://doi.org/10.12944/CWE.5.2.13>.
- Sajil Kumar, P. J., Elango, L., & James, E. J. (2013). Assessment of hydrochemistry and groundwater quality in the coastal area of South Chennai, India. *Arabian Journal of Geosciences*, 7(7), 2641–2653. <https://doi.org/10.1007/s12517-013-0940-3>
- Salem, I. B., Nazzal, Y., Howari, F. M., Sharma, M., Mogaraju, J. K., & Xavier, C. M. (2022). Geospatial assessment of groundwater quality with the distinctive portrayal of heavy metals in the United Arab Emirates. *Water*, 14, 879. <https://doi.org/10.3390/w14060879>
- Sapna, K., Thangavelu, A., Mithran, S., & Shanthi, K. (2018). Spatial analysis of river water quality using inverse distance weighted interpolation in noyyal watershed in Coimbatore, Tamilnadu, India. *Research Journal of Life Sciences, Bioinformatics, Pharmaceutical and Chemical Sciences*, 4(1), 150.
- Sapna, K., Thangavelu, A., & Kaarmuhil, S. P. (2020a). Surveillance of groundwater quality of selected rural and industrial areas of Coimbatore: A GIS approach. *IOP Conference Series: Materials Science and Engineering*, 762, 955. <https://doi.org/10.1088/1757-899X/955/1/012083>
- Sapna, K., Thangavelu, A., & Sujithra, B. (2020b). GIS based evaluation of contamination of fluoride in groundwater quality and occurrence of dental fluorosis in Coimbatore district, TamilNadu, India. *IOP Conference Series: Materials Science and Engineering*, 955. <https://doi.org/10.1088/1757-899X/955/1/012082>
- Satish Kumar, V., Amarender, B., Dhakate, R., et al. (2016). Assessment of groundwater quality for drinking and irrigation use in shallow hard rock aquifer of Pudunagaram, Palakkad District Kerala. *Applied Water Science*, 6, 149–167. <https://doi.org/10.1007/s13201-014-0214-6>
- Sefie, A., Aris, A. Z., Ramli, M. F., Narany, T. S., Shamsuddin, M. K. N., et al. (2018). Hydrogeochemistry and groundwater quality assessment of the multilayered aquifer in Lower Kelantan Basin, Kelantan, Malaysia. *Environmental Earth Sciences*, 77, 397.
- Shanmugamoorthy, M., Subbaiyyan, A., Velusamy, S., & Man, S. (2022). Review of groundwater analysis in various regions in Tamil Nadu, India. *KSCE Journal of Civil Engineering*, 26, 3204. <https://doi.org/10.1007/s12205-022-1412-7>
- Singh, P., & Khan, I. A. (2011). Ground water quality assessment of Dhankawadi ward of pune by using GIS. *International Journal of Geomatics and Geosciences*, 2(2), 688–703.
- Singh, P. K., Tiwari, A. K., Panigarhy, B. P., & Mahato, M. K. (2013). Water quality indices used for water resources vulnerability assessment using GIS technique: A review. *International Journal of Earth Sciences and Engineering*, 6(6–1), 1594–1600.
- Su, Z., Wu, J., He, X., & Elumalai, V. (2020). Temporal changes of groundwater quality within the groundwater depression cone and prediction of confined groundwater salinity using Grey Markov model in Yinchuan area of northwest China. *Expo Health*. <https://doi.org/10.1007/s12403-020-00355-8>
- Sundaray, S. K., Panda, U. C., Nayak, B. B., & Bhatta, D. (2006). Multivariate statistical techniques for the evaluation of spatial and temporal variations in water quality of the Mahanadi river –estuarine system (India) – A case study. *Environmental Geochemistry and Health*, 28, 317–330.
- Thangavelu, A. (2013). Mapping the groundwater quality in Coimbatore city, India Based on Physico-Chemical Parameters. *International Journal of Environmental Science, Toxicology and Food Technology*, 3(4), 32–40.
- Thangavelu, A., Sapna, K., & Prabitha, A. (2019). Assessment of fluoride hazard in groundwater of Palghat District, Kerala: a GIS approach. *International Journal of Environment and Pollution*, 66(1–3), 187–211.
- Thangavelu, A., Manoj, K., Sapna, K., & Najla, P. (2021). Monitoring the substantial metal analysis and HMPI in groundwater from village and nearby developed areas of Kannur Region: A gis study. *Pollution Research*, 40(4), 1293–1300.
- Tiwari, A. K., Singh, A. K., & Mahato, M. K. (2018). Assessment of groundwater quality of 636 Pratapgarh district in India for suitability of drinking purpose using water quality index 637 (WQI) and GIS technique. *Sustainable Water Resources Management*, 4, 601–616.
- USEPA (1975). Manual of water well construction practices. EPA-570/9-75-001. Office of Water Supply, Washington, DC, 156 p.
- Vasanthavigar, M., Srinivasamoorthy, K., Vijayaragavan, K., Ganthi, R. R., Chidambaram, S., et al. (2010). Application 798 of water quality index for groundwater quality assessment: Thirumanimuttar sub-basin, Tamilnadu, India. *Environmental Monitoring Assessment*, 171(1–4), 595–609. <https://doi.org/10.1007/s10661-009-1302-1>
- Verma, P., Singh, P. K., Sinha, R. R., & Tiwari, A. K. (2020). Assessment of groundwater quality status by using water quality index (WQI) and geographic information system (GIS) approaches: A case study of the Bokaro District, India. *Applied Water Science*, 10(1), 1–16. <https://doi.org/10.1007/s13201-019-1088-4>
- Wang, D., Wu, J., Wang, Y., & Ji, Y. (2020). Finding high-quality groundwater resources to reduce the hydatidosis incidence in the Shiqu County of Sichuan Province, China: Analysis, assessment, and management. *Expo Health*, 12, 307–322. <https://doi.org/10.1007/s12403-019-00314-y>

WHO. (2006). *Protecting groundwater for health, managing the quality of drinking-water sources*. IWA Publishing.

Zhang, X., Miao, J., Hu, B. X., Liu, H., Zhang, H., et al. (2017). Hydrogeochemical characterization and groundwater quality assessment in intruded coastal brine aquifers (Laizhou Bay, China). *Environmental Science and Pollution Research*, 24, 21073–21090.

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