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ORIGINAL PAPER

Determining the Minimum Suitable Number of Water Quality Indicators to Improve the EWQI Water Quality Assessment Model in Baojixia Irrigation District, Northwest China

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Abstract

Selecting a suitable number of parameters for water quality assessment can make the assessment cost-effective. The current investigation involved the collection of 64 groundwater samples from the Baojixia irrigation district located in China. These samples were then analyzed for 17 water quality parameters. Two minimum entropy water quality index ($EWQI_{min}$) models were proposed by selecting the key parameters from the analyzed water quality parameters through principal component analysis (PCA) and multiple linear regression analysis (MLR), correspondingly. Then, the two proposed $EWQI_{min}$ models were utilized to evaluate the water quality within the study area. The findings revealed that the $EWQI_{min-MLR}$ model, which comprised 5 key parameters (total dissolved solids (TDS), sodium (Na^+), nitrate (NO_3^-), total hardness (TH), and fluorine (F^-), exhibited better performance in groundwater quality evaluation. This model demonstrated a higher coefficient of determination ($R^2 = 0.953$, $P < 0.001$), coupled with lower values of Root Mean Square Error (RMSE, 4.948) and Percentage Error (PE, 5.823%) when compared to the $EWQI_{min-PCA}$ model consisting of 6 key parameters including TDS, Na^+, TH, chloride (Cl^-), nitrite (NO_2^-) and chemical oxygen demand (COD_{Mn}). Furthermore, the groundwater quality in the Baojixia irrigation district was considered a moderate quality category, with the eastern region displaying poorer water quality in comparison to the western area. The comparison of $EWQI_{min}$ and EWQI indicated that the developed $EWQI_{min}$ model was a suitable and effective method as its performance in evaluating groundwater quality within the Baojixia irrigation district is excellent. The results of this research have significant implications for the effective management of groundwater and the promotion of sustainable development of water resources in future investigations.

Keywords Key Parameters Selection · Principal Component Analysis · Stepwise Multiple Linear Regression · Baojixia Irrigation District · Groundwater Quality Assessment

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Introduction

Groundwater serves as a vital natural resource that is intricately linked to various aspects of human life, such as domestic drinking, agricultural irrigation, and economic production (Wu et al. 2020; Agbasi et al. 2023; Li et al. 2024). According to numerous reports, around 33% of the world's population depends on groundwater, which has been crucial in facilitating the expansion of the global population, currently standing at 7.5 billion individuals as of 2018 (Falkenmark 2005; He et al. 2019; Li et al. 2019). Ensuring access to uncontaminated and secured underground water is a crucial necessity for upholding human well-being and promoting socially sustainable progress, especially in arid and semi-arid areas with inadequate precipitation and surface water resources (Gao et al. 2020; Zhang et al. 2021a). Unfortunately, in recent years, both the volume and excellence of groundwater have been adversely affected by the rapid pace of economic development, population expansion, as well as certain anthropogenic activities, leading to a global predicament (Ahmed et al. 2019; Khan et al. 2020; Mohammadi et al. 2020; Liu et al. 2021). To comprehend the present condition and identify current water quality trends, water quality assessment emerges as an effective approach. Conducting water quality assessments enables us to acquire valuable insights into the current state of water quality and monitor any changes that may occur over time. By employing appropriate assessment models and techniques, researchers and policymakers can make informed decisions regarding the management and preservation of groundwater resources. Consequently, water quality assessment serves as an essential tool for addressing the challenges posed by deteriorating groundwater quality.

Numerous methodologies are available for conducting water quality assessments, such as the fuzzy analytical hierarchy process, set pair analysis, numerical modeling, and multivariate statistical analysis (Ali et al. 2017; Zhang et al. 2021a; Yang et al. 2023; Ayejoto et al. 2023). The water quality index (WQI) is the most commonly employed method for evaluating water quality among these approaches (Singh et al. 2023). The WQI utilizes an aggregation function to convert an assortment of water quality data into a singular measure that represents the comprehensive state of the water (Kangabam et al. 2017; Nath et al. 2018; Wu et al. 2018a; Gao et al. 2020). The effectiveness of this index in assessing water quality has been globally recognized (Benouara et al. 2016; Sutadian et al. 2016). Nevertheless, the conventional WQI possesses certain limitations, such as its inflexible framework and reliance on subjective weights for evaluating the parameters (Abtahi et al. 2015; Gao et al. 2020). Consequently, considerable efforts have been undertaken to enhance the WQI. Li et al. (2010) developed the formulae of entropy-weighted water quality index (EWQI) by incorporating entropy weights, thereby eliminating the subjectivity associated with parameter weighting in the traditional WQI. Since then, the EWQI has been successfully employed in numerous studies, demonstrating its reliability in assessing water quality (Ali et al. 2017; Islam et al. 2020). Nonetheless, the EWQI involves a large number of water quality parameters in the assessment, making it time-consuming and costly to analyze so many parameters in the laboratory (Xu et al. 2018). Therefore, there is a need to refine the assessment process by selecting a suitable number of parameters that ensure both accuracy and cost-effectiveness.

Incorporating data reduction methods in water quality assessment helps in finding an appropriate set of parameters. For instance, Li et al. (2012) applied the concept of rough set attribute reduction in selecting appropriate water quality assessment parameters and proposed the rough set-TOPSIS method for groundwater quality evaluation. The WQI_{min} method, created by Pesce and Wunderlin (2000), evaluates water quality by choosing various essential factors. The development of the WQI_{min} was based on the WQI, and there have been reports of strong correlations between the WQI_{min} and WQI results (Sánchez et al. 2007). The utilization of the WQI_{min} approach has demonstrated its advantages in decreasing the expense associated with assessing water quality (Kannel et al. 2007; Nong et al. 2020). Nevertheless, the WQI_{min} model may select different numbers of water quality parameters for the assessment. Simoes et al. (2008) conducted a study that exemplifies this concept and employed the WQI_{min} method to evaluate the degradation of water quality in São Paulo State, Brazil. The evaluation focused solely on dissolved oxygen, turbidity, and total phosphorus. Meanwhile, the water quality of the Dongjiang River, China was evaluated using the WQI_{min} method by Sun et al. (2016). This method considered factors such as the pH, temperature, total suspended solids, ammonium, and nitrate. Moreover, previous WQI_{min} models have typically used only one method to choose the key parameters, which may lead to an overestimation of the water quality (Kannel et al. 2007). Up to the present, there are few reports on the minimum EWQI ($EWQI_{min}$) model for evaluating groundwater quality, and the performance of the $EWQI_{min}$ model for groundwater assessment is still unclear. Given this, the $EWQI_{min}$ model was proposed in this study for groundwater quality assessment.

The Baojixia irrigation district, located in Shaanxi Province, China, is acknowledged as the largest water diversion irrigation area within the Wei River Basin (Zhang et al. 2021b), with an extensive irrigated area spanning 1890 km^2 (Cheng et al. 2019). This area has been actively involved in water diversion since 1972. Several diversion canals have been constructed to support agriculture in the area (Wu et al. 2012). In the Baojixia irrigation district, the primary water source for irrigation is the Wei River, supplemented by groundwater resources. Recently, the rise in water usage in the upstream area of the Wei River, coupled with ongoing ecological degradation, has resulted in decreased river runoffs and a scarcity of surface water resources, particularly in the dry seasons. As a consequence, the exploitation of groundwater in the Baojixia irrigation district has been increasing recently to meet the irrigation purpose (Minhas et al. 2019). Groundwater is critical for human consumption and agricultural irrigation in this area. For the water quality of the study area, most researchers tend to explore its water quality impact factors, the water quality assessment is currently limited to either a single-indicator analysis or a simple comprehensive analysis of multiple indicators.

However, these methods are subjective and time-consuming and do not provide more accurate and valuable information. Therefore, it is imperative to find a comprehensive, accurate, convenient, and efficient method to understand the water status and assess the water quality in the Baojixia irrigation region.

Hence, the objectives of this study were to (1) identify key parameters from the various groundwater quality indicators using principal component analysis (PCA) and stepwise multiple linear regression (MLR) to build $EWQI_{min-PCA}$ and $EWQI_{min-MLR}$ models, respectively, (2) compare the EWQI, $EWQI_{min-PCA}$ and $EWQI_{min-MLR}$ models and determine the optimal model for water quality assessment, and (3) comprehensively assess the groundwater quality and its spatial variability in the Baojixia irrigation district using the best $EWQI_{min}$ model. This study is to furnish valuable and dependable information for assessing the quality of groundwater in the Baojixia irrigation district. Furthermore, it can serve as a reference for future studies, thereby contributing to the attainment of sustainable water resource development.

Materials and Methods

Study Area

The Baojixia irrigation district is situated in the western region of the Guanzhong Basin in Shaanxi Province, Northwest China (Fig. 1). It holds the distinction of being the largest irrigation district in Shaanxi Province and ranks among the top ten irrigation districts in China. Stretching across a length of 181 km from east to west and a width of 14 km from north to south, the Baojixia irrigation district encompasses a significant expanse. The irrigation water for this district is sourced from the Wei River, and the effective irrigation area spans approximately 1890 km^2 (Gao et al. 2021).

The Baojixia irrigation district falls within the semi-humid zone of the monsoon climate, characterized by distinct seasonal patterns. This region experiences severe droughts during the spring (March-May) and winter (December-February) while experiencing relatively heavy precipitation in the summer (June-August) and autumn (September-November) seasons. The average annual precipitation in the area is recorded at 566 mm, accompanied by an average annual evaporation of 1110 mm. The average temperature is around 14 °C, and the frost-free period extends for approximately 220 days, with frost occurring between December and March (Wang et al. 2023a). The geographical characteristics of this research area consist of a variety of features, such as the alluvial plains of the Wei River and its tributaries, terraces made of loess, alluvial plains in the Piedmont region, and areas with low hills. Pore water is found mainly in sandstone aquifers combined with pebbles, gravel, and clay, and serves as the main supplier of groundwater in the area. Groundwater recharge primarily occurs through atmospheric precipitation and lateral runoff, while artificial extraction, discharge into the Wei River, and evaporation are the main processes through which groundwater is discharged. As one moves from the loess hill to the Weihe alluvial plain, the groundwater level gradually decreases and the overall flow direction of groundwater is from northwest to southeast (Feng et al. 2020). The soils in the Baojixia irrigation district are fertile, characterized by two distinct types: Wei River alluvial soils beneath the Loess Plateau and loess on the upper part of the Loess Plateau. The fertile soils create a conducive atmosphere for farming, enabling the growth of diverse crops like wheat, corn, cotton, canola, and economically important fruit groves. The agricultural productivity in this irrigation area plays a crucial role in ensuring food security within Shaanxi Province.

Sample Collection and Analysis

During August in the year 2020, a total of 64 samples of groundwater were gathered from the designated region. The exact positions of the sites where the samples were taken were meticulously documented with the aid of a portable GPS apparatus. All samples were obtained by pumping water from existing hand pumps or boreholes with depths not exceeding 100 m. Pumping was carried out for 3 min before the actual sampling process. Each sample was carefully collected in two polyethylene bottles, which had been rinsed with raw water two to three times before sampling. To ensure the stability and reliability of heavy metal analysis, a small amount of HNO_3 was added to one of the two bottles for each of the samples. After sampling, the bottles were immediately sealed, labeled, and stored in a refrigerator set at 4 °C for subsequent laboratory analysis. A total of 17 parameters were measured in the collected groundwater samples. Among the measured parameters analyzed, the pH value was obtained directly onsite using a portable water quality device (OTT HydrolabDS5X). The total hardness (TH) was determined by employing the EDTA titration method, while total dissolved solids (TDS) were quantified using the drying and weighing method. The concentrations of sodium (Na^+) and potassium (K^+) were ascertained using flame atomic absorption spectrophotometry. The EDTA titrimetric method was utilized to quantify calcium (Ca^{2+}), magnesium (Mg^{2+}), and ammonium (NH_4^+). The levels of carbonate (CO_3^{2-}) and bicarbonate (HCO_3^-) were determined by alkalinity titration. Sulfate (SO_4^{2-}), chloride (Cl^-), nitrite (NO_2^-), nitrate (NO_3^-), and fluoride (F^-) were analyzed using Ion Chromatography. Lastly, arsenic

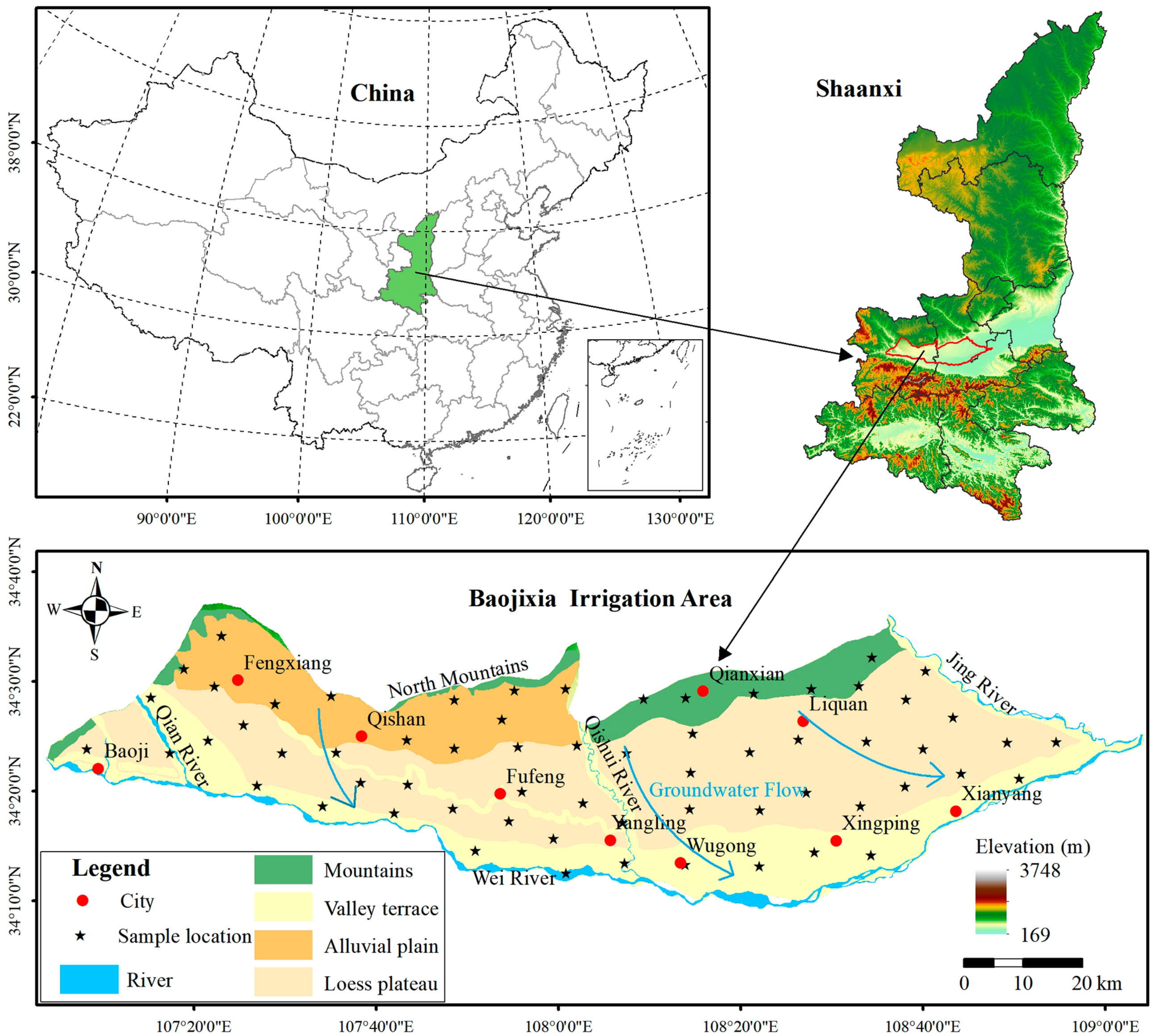


Fig. 1 Location of study area and groundwater sampling sites

(As) was measured through plasma emission spectrometry (ICAP6300).

Furthermore, the chemical oxygen demand (COD_{Mn}) was examined by employing the potassium permanganate index technique. The laboratory conducted all the necessary analyses in accordance with the quality assurance and quality control procedures specified in the national standards established by the Ministry of Environmental Protection of the People's Republic of China (2009). Moreover, the precision of the physicochemical examination was evaluated by computing the charge equilibrium discrepancy (CBE, %) for every groundwater specimen (Eq. 1), within a permissible range of plus or minus 5%. The findings showed that all the specimens were within the acceptable range, suggesting that the precision of the conducted physicochemical analysis in this research was adequate.

$$\mathrm{CBE}(\%) = \frac{\sum \mathrm{Cations} - \sum \mathrm{Anions}}{\sum \mathrm{Cations} + \sum \mathrm{Anions}} \tag{1}$$

Calculations and Establishment of the $EWQI_{min}$

The $EWQI_{min}$ model is established through a five-step process depicted in Fig. 2. Initially, data from 38 groundwater samples, distributed across the study area, were used as

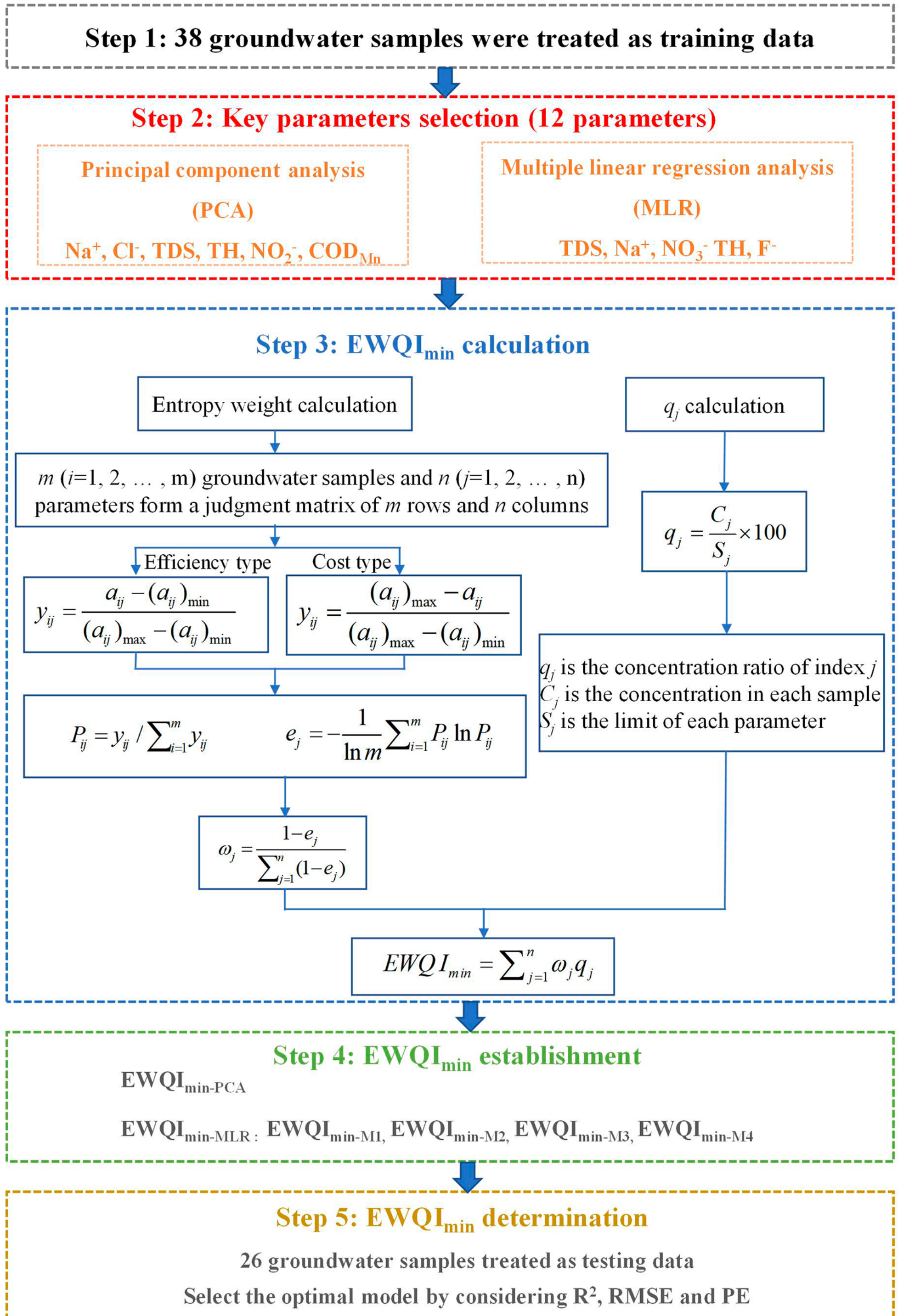


Fig. 2 Steps for calculation and establishment of the $EWQI_{min}$ model

the training set for key parameter selection. The parameters considered included pH, TDS, TH, Na^+, Cl^-, SO_4^{2-}, NO_3^-, NO_2^-, NH_4^+, F^-, COD_{Mn}, and As.

In the second step, PCA and MLR were employed to identify the minimum number of appropriate water quality parameters for the assessment. PCA was conducted to extract the significant principal components (PCs) using the Kaiser criteria. Subsequently, the primary groundwater quality parameters with high loadings on the selected PCs were retained as the minimum number of parameters for water quality assessment. MLR was performed using a stepwise approach, with the EWQI as the dependent variable and the physicochemical parameters as independent variables. The key parameters for water quality assessment were determined by considering the physicochemical parameters that demonstrated optimal performance in formulating the MLR model.

After the key parameters were selected using PCA and MLR, the third step involved calculating the $EWQI_{min}$ values based on these selected parameters. To verify the reliability of the developed $EWQI_{min}$ models, the remaining 26 groundwater samples, distributed across the study area, were used as testing data to validate the established $EWQI_{min-PCA}$ and $EWQI_{min-MLR}$ models in the fourth step. Finally, the performance of the models was evaluated based on the coefficient of determination (R^2), while the predictive accuracy of the different $EWQI_{min}$ models was assessed using the Root Mean Square Error (RMSE) and Percentage Error (PE). The PE was calculated according to the method of Canfield and Bachmann (1981) as follows (Eq. 2):

$$\mathrm{PE} = \sum |P/O - 1| \times 100/n \tag{2}$$

where P represents the minimum EWQI value according to the chosen parameters and O represents the EWQI value considering all parameters.

The groundwater quality in the current research is categorized into five grades based on the $EWQI_{min}$ values (Yang et al. 2023), including excellent quality (< 25), good quality (25–50), moderate quality (50–100), poor quality (100–150) and very poor quality (> 150).

Data Processing

The Kaiser-Meyer-Olkin (KMO) test (KMO > 0.6, $p < 0.001$) and Bartlet test were conducted to ensure the suitability of the data for PCA. These tests help assess the adequacy of the data for the PCA and ensure that the variables are sufficiently correlated. Additionally, for the MLR analysis, the data underwent a preprocessing step. Specifically, a log transformation was applied to the data, following the methods outlined in a previous study conducted by the researchers (Mu et al. 2023). This preprocessing step aimed to enhance the accuracy and reliability of the MLR analysis. The IBM SPSS 25 software Package and Origin 2021 were utilized for all the data processing. The geospatial map was generated using ArcGIS 10.7 based on the Kriging interpolation, which allowed for the visualization of the spatial patterns of water quality parameters within the study area.

Results

Physicochemical Characteristics of Groundwater

The minimum (Min), maximum (Max), mean (Mean), standard deviation (SD), and coefficient of variation (CV) of the physicochemical parameters were calculated and listed in Table 1. The pH values of the groundwater ranged from 7.65 to 8.82, with an average value of 8.22, indicating that the groundwater samples in the Baojixia irrigation district were generally slightly to strongly alkaline. The concentrations of TDS were between 280.00 and 1652.00 mg/L, with an average concentration of 640.23 mg/L. The TH concentration of the groundwater samples exhibited a wide range of variation, from 95.10 to 651.00 mg/L, with a mean concentration of 333.17 mg/L. The categorizations of TDS and TH of the groundwater suggested that the majority of the water

Table 1 Statistical summary of the chemical composition of groundwater in the study region

Parameters	Unit	Chinese Standard (grade III) [a]	Min	Max	Mean	SD	CV (%)
pH	/	$6.5 \leq pH \leq 8.5$	7.65	8.82	8.22	0.30	3.63
TDS	mg/L	1000	280.00	1652.00	640.23	261.26	40.81
TH	mg/L	450	95.10	651.00	333.17	139.48	41.86
Na^+	mg/L	200	11.70	396.00	100.86	79.97	79.29
K^+	mg/L	/	0.35	20.50	1.90	3.26	171.33
Ca^{2+}	mg/L	/	14.00	156.00	57.86	36.67	63.38
Mg^{2+}	mg/L	/	14.60	92.40	45.86	19.87	43.34
CO_3^{2-}	mg/L	/	0.00	30.00	3.13	7.22	230.91
HCO_3^-	mg/L	/	195.00	793.00	466.39	115.68	24.8
Cl^-	mg/L	250	6.00	238.00	51.46	50.40	97.94
SO_4^{2-}	mg/L	250	4.80	183.00	56.54	51.64	91.33
NO_3^-	mg/L	88.50	1.25	671.00	66.81	100.84	150.93
NO_2^-	mg/L	3.29	0.002	1.641	0.073	0.246	338.08
NH_4^+	mg/L	0.64	0.015	0.150	0.044	0.039	89.86
F^-	mg/L	1	0.26	2.40	0.86	0.53	60.94
COD_{Mn}	mg/L	3	0.24	3.60	0.74	0.58	77.46
As	mg/L	0.01	0.0005	0.0060	0.0016	0.0011	65.19

[a] Standards for groundwater quality of the People's Republic of China

samples gathered from the Baojixia irrigation district met the criteria established for groundwater excellence in China.

The analysis of cation concentrations in the groundwater revealed the following order: $Na^+ > Ca^{2+} > Mg^{2+} > K^+ > NH_4^+$. Among these measured cations, Na^+ was found to be the most abundant in the groundwater of the Baojixia irrigation district, ranging from 11.70 to 396.00 mg/L. It was worth noting that the mean value fell within the standard limit of 200 mg/L for drinking water in China. The levels of Ca^{2+} and Mg^{2+} were found to be within the range of 14.00 to 156.00 mg/L and 14.60 to 92.40 mg/L, respectively. Moreover, the K^+ concentration varied between 0.35 and 20.50 mg/L, with an average of 1.90 mg/L. NH_4^+ levels ranged from 0.015 to 0.150 mg/L, averaging at 0.044 mg/L.

The anion concentrations of the groundwater were arranged in the following sequence: $HCO_3^- > NO_3^- > SO_4^{2-} > Cl^- > CO_3^{2-} > NO_2^-$. The CO_3^{2-} concentrations ranged from 0.00 to 30.00 mg/L, while the HCO_3^- concentration ranged from 195.00 to 793.00 mg/L, averaging 466.39 mg/L. The NO_3^- concentration ranged from 1.25 to 671.00 mg/L, with a mean value of 66.81 mg/L, which fell within the acceptable limit according to Chinese regulations of 88.5 mg/L. The concentration of NO_2^- ranged from 0.002 to 1.641 mg/L, averaging at 0.073 mg/L, which falls comfortably within the permissible standard in China (3.29 mg/L). The concentration of SO_4^{2-} ranged from 4.80 to 183.00 mg/L, with an average of 56.54 mg/L. The concentration of Cl^- ranged from 6.00 to 238.00 mg/L, with an average of 51.46 mg/L. In this research, both the SO_4^{2-} and Cl^- were found to be below the acceptable threshold of 250 mg/L.

Although the COD_{Mn} of the groundwater reached a peak of 3.60 mg/L, surpassing China's drinking water limit of 3 mg/L, the average value remained relatively low at 0.74 mg/L. The levels of F^- and As varied between 0.26 and 2.40 mg/L and 0.0005 to 0.0060 mg/L, respectively, with mean concentrations of 0.86 and 0.0016 mg/L, correspondingly.

Additionally, a Piper diagram was generated to uncover the hydrochemical attributes of the groundwater samples (Fig. 3). The diagram illustrates the hydrochemical facies displayed by the 64 groundwater samples in the current investigation. On the cation plot, the majority of samples fell in the middle of the plot (Zone B), suggesting that there is no notable cation dominance in the groundwater of the Baojixia irrigation district. Furthermore, around 23% of the groundwater samples displayed diminished levels of calcium, manifesting in Zone D situated at the lower right

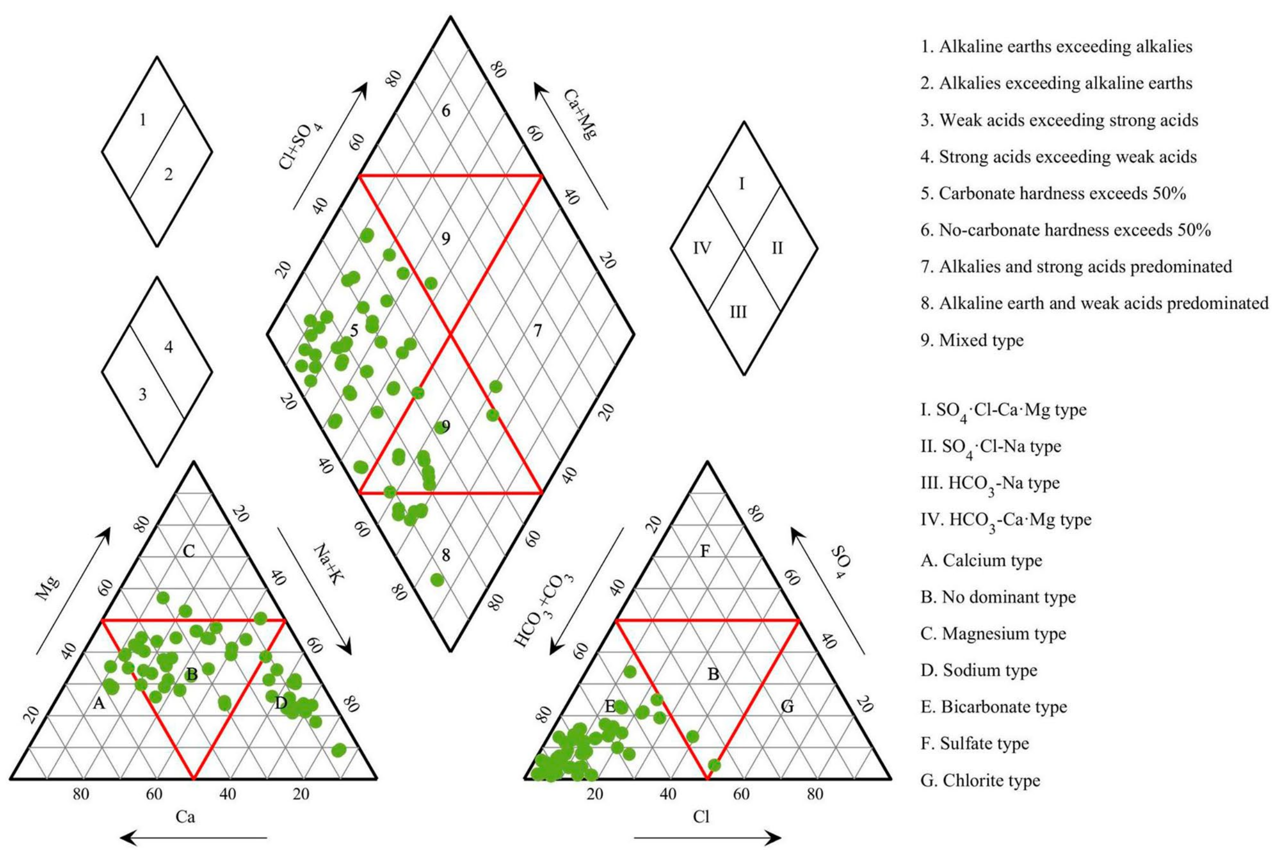


Fig. 3 Piper diagram representing groundwater types in the Baojixia irrigation district

section. In contrast, Zone A had only four sampling sites with comparatively elevated levels of calcium. According to the anion diagram, the majority of the samples were found in Zone E, exhibiting elevated levels of the HCO_3^-. Only two samples were located in Zone B, while no samples were observed in Zone F or Zone G. These findings indicate that the groundwater in the Baojixia irrigation district is primarily dominated by HCO_3^-, resulting from the weathering of lithology rich in carbonates. Furthermore, the comprehensive features of groundwater composition can be acquired by utilizing the diamond of the Pieper diagram. According to Fig. 3. In the groundwater of the Baojixia irrigation district, there were four primary chemical types present. These included the SO_4·Cl-Ca·Mg type in Zone I, SO_4·Cl-Na type in Zone I, HCO_3-Na type in Zone III, and HCO_3-Ca·Mg type in Zone IV. The majority of samples were found in Zone IV, with Zone III following closely behind. This suggests that the predominant hydrochemical type of groundwater in the Baojixia irrigation district was HCO_3-Ca·Mg type and HCO_3-Na type. However, a single sample was distributed in Zone I and Zone II, respectively.

Establishment of the $EWQI_{min}$ Models

PCA was employed in this study to examine the relationships between geochemical variables by reducing the complexity of the parameters (Hu et al. 2013). The primary objective was to identify the key factors that influence groundwater chemistry. Table 2 displayed the results of the PCA analysis, which yielded four principal components based on the Kaiser criteria (PCs whose eigenvalues are greater than 1 will be retained), resulting in a cumulative contribution of 80.38%. PC1, accounting for 32.08% of the total variance, exhibited significant loadings on Na^+, Cl^- and TDS. PC2, explaining 25.14% of the total variance, displayed a strong loading on TH. PC3 accounted for 14.46% of the total variance and showed notable loadings on NO_2^- and COD_{Mn}. On the contrary, PC4 contributed only 8.70% of the total variance and did not display any substantial loadings on the groundwater parameters (Fig. 4). Consequently, the primary indicators selected for evaluating groundwater quality in the Baojixia irrigation district using the $EWQI_{min-PCA}$ model were Na^+, Cl^-, TDS, TH, NO_2^- and COD_{Mn}, which were represented in the first three principal components (PC1, PC2, and PC3).

Table 3 summarizes the findings of the multiple linear regression analysis conducted on the groundwater quality parameters in the Baojixia irrigation district. The findings revealed that TDS had the most significant impact on the $EWQI_{min}$ based on the data, as indicated by an R^2 value of 0.548 ($P<0.001$). When the parameters of Na^+, NO_3^-, and TH were sequentially put into the model, the R^2 values of the regression model increased significantly to 0.802, 0.828, and 0.865 ($P<0.001$), respectively. In addition, the inclusion of F^- and COD_{Mn} further enhanced the performance of the model, resulting in R^2 values of 0.908 and 0.963 ($P<0.001$), respectively. Hence, the TDS, Na^+, NO_3^-, TH, F^-, and COD_{Mn} were chosen as the key factors in the $EWQI_{min-MLR}$ method to assess the water quality of the Baojixia irrigation district.

The performance of the $EWQI_{min-MLR}$ model, established with the six selected basic indicators, was comprehensively evaluated using R^2, RMSE, and PE values based on the testing data. The R^2 values can be significantly improved by increasing the number of indicators selected through regression selection analysis, as demonstrated in Table 4. The results revealed that the M1, M2, and M3 models exhibited relatively low R^2 values (0.535, 0.782, and 0.811, $P<0.001$), whereas the R^2 values of the M4, M5, and M6 models surpassed 0.90. Upon comparing the M4, M5, and M6 models,

Table 2 Variance explained by the main components

Component	Initial eigenvalues			Extraction sums of squared loadings		
	Total	Variance contribution (%)	Cumulative variance contribution (%)	Total	Variance contribution (%)	Cumulative variance contribution (%)
PC1	3.85	32.08	32.08	3.85	32.08	32.08
PC2	3.02	25.14	57.22	3.02	25.14	57.22
PC3	1.74	14.46	71.68	1.74	14.46	71.68
PC4	1.05	8.70	80.38	1.05	8.70	80.38
PC5	0.79	6.58	86.96	/	/	/
PC6	0.58	4.83	91.79	/	/	/
PC7	0.45	3.71	95.50	/	/	/
PC8	0.20	1.69	97.18	/	/	/
PC9	0.16	1.30	98.48	/	/	/
PC10	0.13	1.04	99.52	/	/	/
PC11	0.05	0.45	99.97	/	/	/
PC12	0.01	0.03	100.00	/	/	/

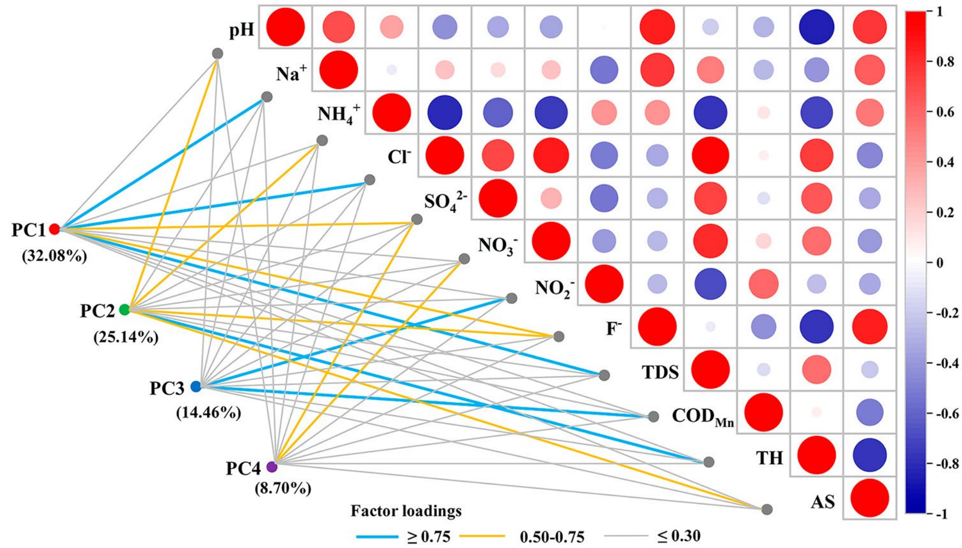


Fig. 4 Selection of key parameters based on the PCA.

Table 3 Key parameter selection of the $EWQI_{min}$ models from the multiple linear regression model based on the training data

Model	Linear model	R^2	P
M1	$-0.371^* + 0.762^*\lg(TDS+1)$	0.548	<0.001
M2	$-0.417^* + 0.744^*\lg(TDS+1) + 4.199^*\lg(Na^+ + 1)$	0.802	<0.001
M3	$-0.298^* + 0.629^*\lg(TDS+1) + 4.630^*\lg(Na^+ + 1) + 0.084^*\lg(NO_3^- + 1)$	0.828	<0.001
M4	$-0.106^* + 0.507^*\lg(TDS+1) + 4.019^*\lg(Na^+ + 1) + 0.114^*\lg(NO_3^- + 1) + 0.359^*\lg(TH+1)$	0.865	<0.001
M5	$-0.040^* + 0.476^*\lg(TDS+1) + 3.450^*\lg(Na^+ + 1) + 0.102^*\lg(NO_3^- + 1) + 0.414^*\lg(TH+1) + 0.218^*\lg(F^- + 1)$	0.878	<0.001
M6	$0.895^* + 0.102^*\lg(TDS+1) + 0.058^*\lg(Na^+ + 1) + 0.111^*\lg(NO_3^- + 1) + 0.019^*\lg(TH+1) + 0.075^*\lg(F^- + 1) + 0.078^*\lg(COD_{Mn} + 1)$	0.963	<0.001

Note: $P < 0.001$

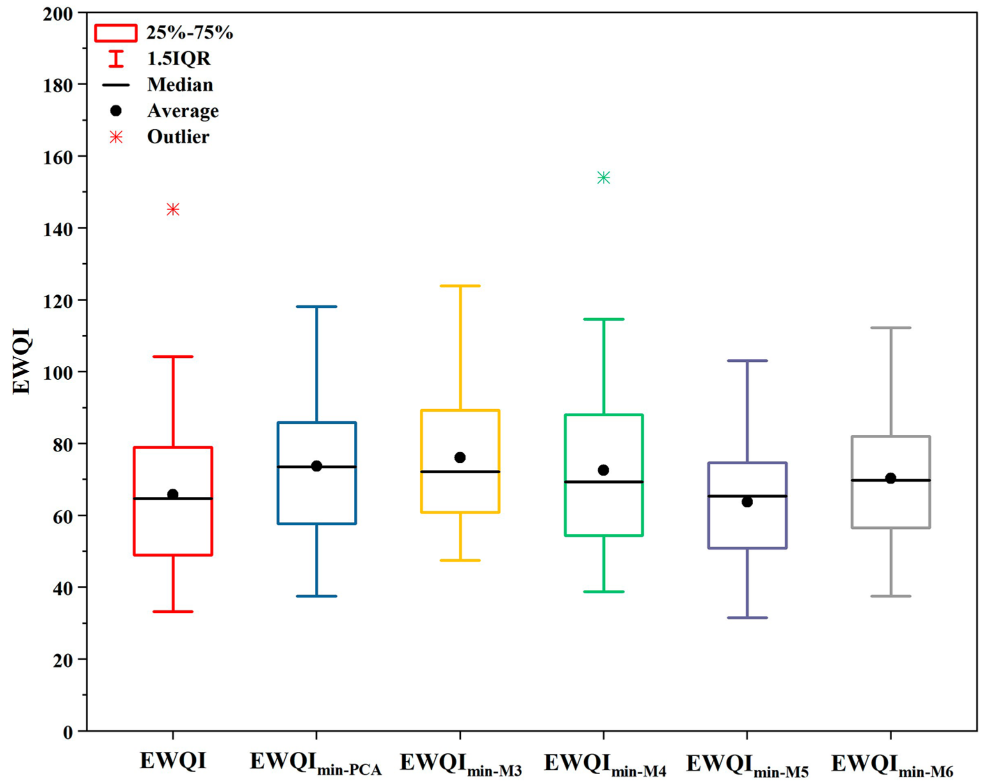
Table 4 Key parameter selection of the $EWQI_{min}$ models from the multiple linear regression based on the testing data

Parameter selection	$EWQI_{min}$				
	Models	R^2	RMSE	PE (%)	P
TDS,	M1	0.535	10.988	12.121	<0.001
TDS, Na^+	M2	0.782	9.945	10.823	<0.001
TDS, Na^+, NO_3^-	M3	0.811	8.232	9.175	<0.001
TDS, Na^+, NO_3^-, TH	M4	0.906	6.253	7.612	<0.001
TDS, Na^+, NO_3^-, TH, F^-	M5	0.953	4.948	5.823	<0.001
TDS, Na^+, NO_3^-, TH, F^-, COD_{Mn}	M6	0.962	5.811	6.879	<0.001

it was found that the M4 model had a slightly lower R^2 value and higher values of RMSE (6.253) and PE (7.612). In addition, the M5 model displayed greater R^2 values (0.953, $P < 0.001$) than the M4 model, along with the lowest values of RMSE (4.948) and PE (5.823%) compared to the M4 and M6 models. Furthermore, the M6 model exhibited the highest R^2 value (0.962, $P < 0.001$), although the RMSE and PE values were only slightly larger than those of the M5 model. Based on a thorough comparison of R^2, RMSE, and PE values, it was concluded that the M5 model exhibited superior performance compared to the other five $EWQI_{min}$ models. Additionally, the M5 model exhibited the closest correlation with the EWQI, as depicted in Fig. 5, further reinforcing its status as the superior model for evaluating groundwater quality in this study.

In summary, the main indicators selected for the $EWQI_{min-PCA}$ model were Na^+, Cl^-, TDS, TH, NO_2^- and COD_{Mn}, while the TDS, Na^+, NO_3^-, TH, and F^- were used as indicators for the $EWQI_{min-MLR}$ model. Based on the entire data set, Fig. 6 shows the relationships between the EWQI model and the $EWQI_{min-PCA}$ model, and between the EWQI model and the $EWQI_{min-MLR}$ model, respectively. As shown in Fig. 6a, there was a close correlation between the $EWQI_{min-PCA}$ model and the EWQI model, as evidenced by the R^2 value of 0.92 ($P < 0.001$) and PE of 10.42%, respectively. Compared with the $EWQI_{min-PCA}$ model, the $EWQI_{min-MLR}$ model showed a higher correlation with the EWQI model, with higher a R^2 value of 0.96 but a lower PE value of 4.75% (Fig. 6b). In addition, the 95% confidence band of the $EWQI_{min-PCA}$ model was slightly wider compared to that of the $EWQI_{min-MLR}$ model. These results

Fig. 5 Comparison of EWQI and $EWQI_{min}$ values based on the training data



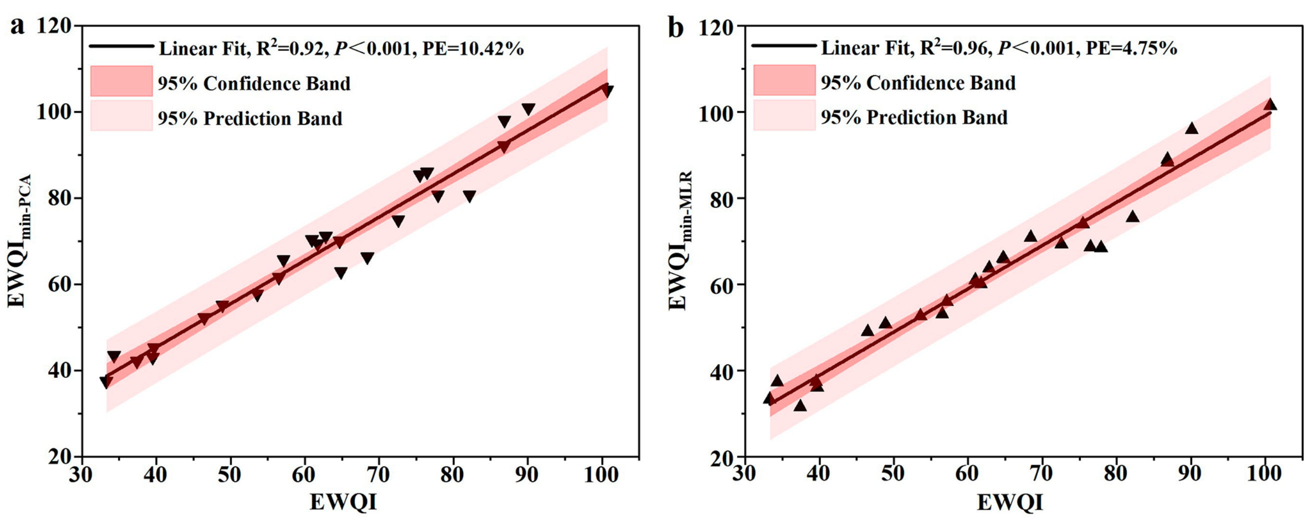


Fig. 6 Relationships between EWQI and $EWQI_{min-PCA}$ and $EWQI_{min-MLR}$ based on the testing data

indicated that the performance of the $EWQI_{min-MLR}$ model was better than that of the $EWQI_{min-PCA}$ model. Thus, considering these findings, it can be determined that the $EWQI_{min-MLR}$ model is more efficient and dependable in assessing the quality of groundwater in this study.

Water Quality Assessment Using the $EWQI_{min}$ Model

Table 5 summarizes the categorization of water quality in the Baojixia irrigation district using the $EWQI_{min}$ approach. According to the $EWQI_{min}$ values, the classification of groundwater can be categorized into five levels, varying from excellent groundwater to very poor groundwater. In the present study, out of the total of 64 groundwater samples, 28.13% were categorized as "good" and 65.63% as "moderate" water quality status. Three samples were classified as "poor" quality and only one sample was categorized as "very poor" types, accounting for a total of 6.25% of the whole samples, while none of the samples fell into the "excellent" category. The findings of this research

Table 5 $EWQI_{min}$ values and groundwater quality types of the samples

EWQI range	Grade	Groundwater type	Number of samples	% of Samples
<25	I	Excellent	0	0
25–50	II	Good	18	28.13
50–100	III	Moderate	42	65.63
100–150	IV	Poor	3	4.69
>150	V	Very poor	1	1.56

indicated that 93.75% of the groundwater samples within the Baojixia irrigation district were deemed appropriate for drinking. Moreover, there was notable disparity in the spatial arrangement of groundwater quality within the Baojixia irrigation district, and the specific distribution of the $EWQI_{min}$ in the research region can be seen in Fig. 7. Generally, the $EWQI_{min}$ values in the western part of the Baojixia irrigation district were significantly lower than those of the eastern part (Fig. 7a), indicating that groundwater in the central and western parts was more suitable for drinking. The distribution of good and moderate quality groundwater samples was widespread throughout the study area, with the good quality samples primarily located in the western part (including Baiji, Fengxiang, Qishan, and Fufeng). On the contrary, the moderate quality samples were concentrated in the eastern area of the Qishui River (including Yangling, Wugong, Qianxian, Lingquan, Xingping, and Xianyang). Nevertheless, the easternmost part of the study area contained groundwater samples of poor and very poor quality, which accounted for a minor portion of the entire region (Fig. 7b).

Discussion

Groundwater Quality and its Impacting Sources

The groundwater quality parameters in the Baojixia irrigation district were generally consistent with the findings of the prior investigation carried out by Feng et al. (2020), with higher concentrations of TDS, TH, and Na^+ in the groundwater. However, in comparison to the results of Chen et al. (2021), it was observed that the groundwater samples in this study showed higher levels of NO_3^-, which might be related to the agricultural fertilization practices employed in the irrigation areas. The findings of this research revealed that the water pollution was worse than before, emphasizing the urgent need for appropriate management measures to safeguard the quality of groundwater in the Baojixia irrigation district. The dominant cation and anion in the Guanzhong Basin, as identified by Gao et al. (2022), were Na^+ and HCO_3^-, respectively, which was consistent with the findings of the current study. The Piper diagram, extensively employed to classify hydrochemical types of groundwater, demonstrates its significance as an effective tool for analyzing the variation and spatial distribution of ions within groundwater (Piper 1944; Liu et al. 2019; Xu et al. 2019). Feng et al. (2020) have analyzed the hydrochemical types in

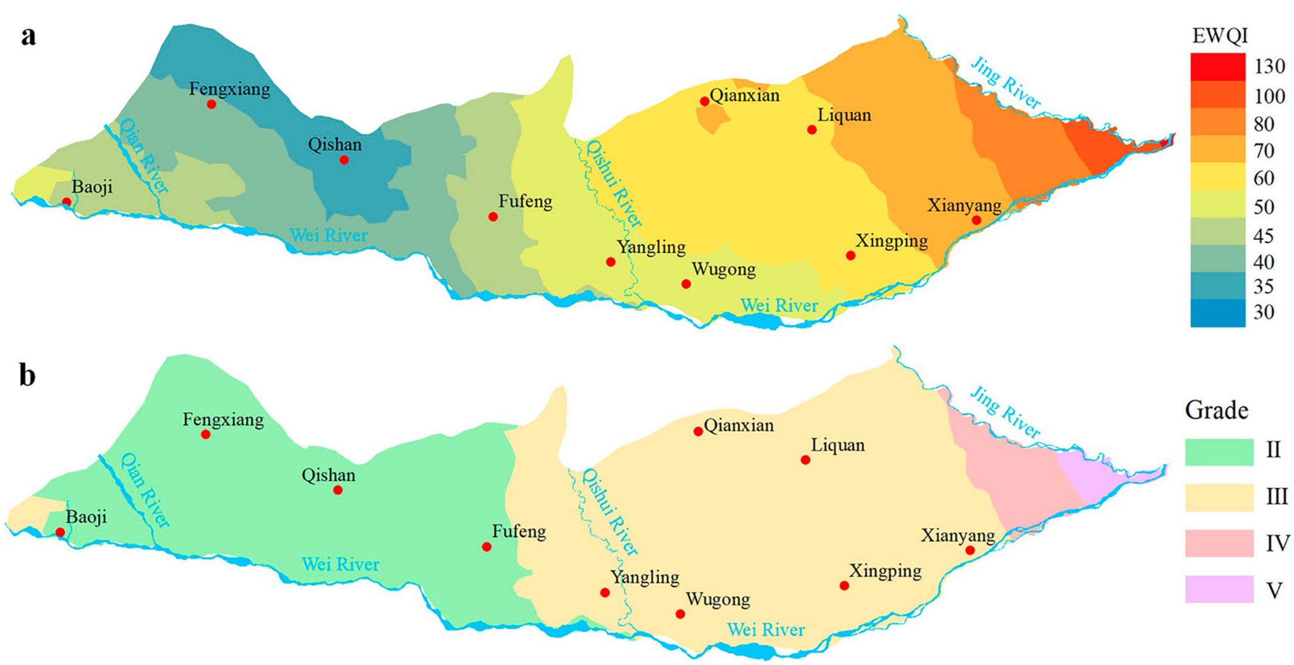


Fig. 7 Spatial variation in groundwater quality in the Baojixia irrigation district based on the $EWQI_{min}$.

the Baojixia irrigation area and found that the HCO_3-Ca·Mg type was mainly concentrated on the Loess Plateau due to the rapid flow of groundwater caused by topographic relief, resulting in mineral dissolution. On the contrary, the HCO_3-Na type was predominantly distributed in low-lying areas and was associated with evaporation and partial cation exchange. HCO_3-Ca·Mg and HCO_3-Na types were the most common in the groundwater samples from the Baojixia irrigation district (Fig. 3), which was consistent with the findings of previous studies (Feng et al. 2020).

Comprehending the origin of groundwater is crucial for the enduring and effective governance of water reserves (Scheiber et al. 2020). The Gibbs diagram serves as a valuable tool in analyzing the main influential factors in the development of water chemistry (Gibbs 1970). It showcases the connections between TDS and $Na^+/(Na^++Ca^{2+})$, as well as the ratio of TDS and $Cl^-/(Cl^-+HCO_3^-)$. In general, the hydrochemical properties of groundwater are mainly affected by precipitation, evaporation, and the process of rock weathering (Sridharan and Nathan 2018; Wu et al. 2018b). As depicted in Fig. 8, the majority of samples had $Na^+/(Na^+ + Ca^{2+})$ and $Cl^-/(Cl^-+HCO_3^-)$ ratios below 0.6 in the Baojixia irrigation district. The majority of groundwater samples fell within the rock dominance zone, while only a few samples were concentrated in the evaporation dominance zone. In addition, the Baojixia irrigation district exhibited elevated levels of Na^+ in groundwater, while Cl^- concentrations were comparatively lower. The water chemistry of all groundwater samples primarily stemmed from rock weathering, as depicted in Fig. 8. The results suggested that the geological aspect played a crucial role in shaping the chemical properties of groundwater within the Baojixia irrigation district. Feng et al. (2020) have reported similar findings in the study area on the western bank of the Qishui River.

The groundwater quality in the Baojixia irrigation district was mainly categorized as “good” or “moderate”, exhibiting a general trend of increasing $EWQI_{min}$ values from west to east. Furthermore, taking into account the Qishui River as the boundary, the groundwater in the western area was predominantly classified as “good”, whereas the water quality in the eastern section was comparatively inferior to that in the western region. The western portion of the research region is located in the Piedmont alluvial fan and loess terrace region, which is known for its high hydraulic conductivity and steep gradient, facilitating the groundwater flow

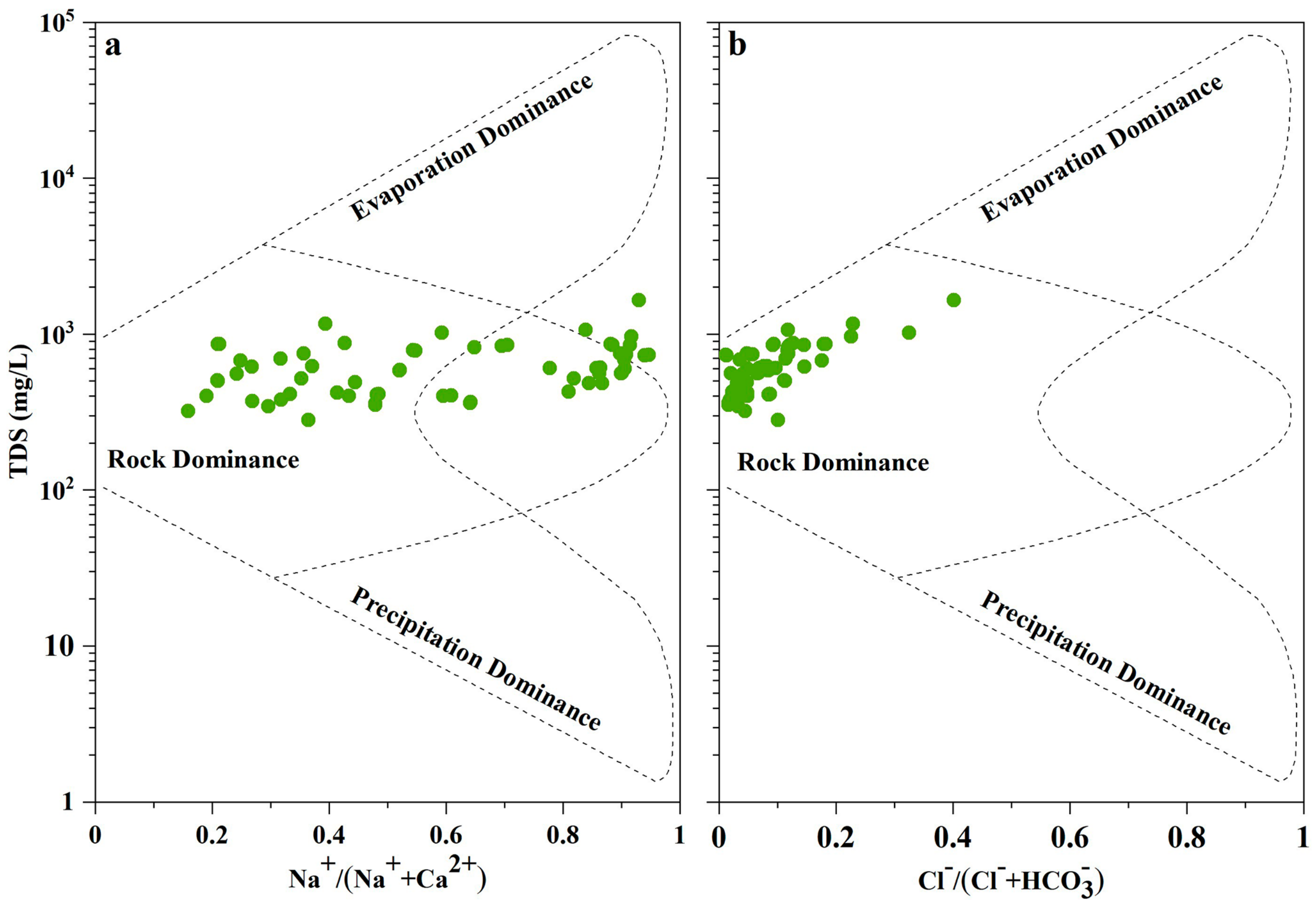


Fig. 8 Gibbs diagram showing the main controlling factors of the groundwater in the Baojixia irrigation district

(Feng et al. 2020; Gao et al. 2022). As a result, the water quality in the western area of the Baojixia irrigation district is more appropriate for human consumption, thus making it a preferable choice for drinking water.

Key Parameters of the $EWQI_{min}$ Model

Based on the R^2, RMSE, and PE values, the $EWQI_{min-MLR}$ model outperformed the $EWQI_{min-PCA}$ model, as indicated by the results in Sect. 3.3.2. Therefore, the $EWQI_{min-MLR}$ model is considered to be more appropriate and dependable for assessing the quality of groundwater in this study. Consequently, the main emphasis of the discussion would be on determining the essential factors for the $EWQI_{min-MLR}$ model through the analysis of multiple linear regression. It is essential that they are representative of other environmental factors and contribute to an efficient evaluation of water quality (Pesce and Wunderlin 2000). The multiple linear regression analysis revealed that the $EWQI_{min}$ model, which includes TDS, Na^+, NO_3^-, TH, and F^-, accounted for a considerable amount of the observed variance in groundwater quality data from the Baojixia irrigation district ($R^2 = 0.953$, $P < 0.001$). This demonstrates the exceptional effectiveness of the model in evaluating groundwater quality.

In the linear regression model, TDS was selected as the first parameter due to its significant contribution to explaining the variations in the EWQI model ($R^2 = 0.548$, $P < 0.001$). TDS indicates the combined amount of inorganic salts and small quantities of dissolved organic substances, and elevated TDS levels can negatively impact human well-being (Tiwari et al. 2016). The TDS concentration recorded in this investigation remained comfortably within the prescribed threshold, averaging 640.23 mg/L. The analysis of spatial distribution showed a progressive rise in TDS levels from the western region to the eastern region of the surveyed area. Baoji, Fengxiang, Qishan, and Fufeng exhibited lower concentrations (TDS < 580 mg/L), while Yangling, Qianxian, Wugong, Liquan, Xingping, and Xianyang displayed higher concentrations (580–1000 mg/L) of TDS. Furthermore, the cities in proximity to the Wei River exhibited notably increased TDS levels, suggesting a high presence of inorganic salts in the groundwater of these urban areas (Fig. 9a).

Na^+ presented the second largest explanatory parameter for the variations in the EWQI model, as illustrated in Fig. 9b. In the Baojixia irrigation district, Na^+ primarily exhibited a band-like distribution, with decreased levels in the western region of the study area and elevated levels in the eastern part. According to Feng et al. (2020), an important rise in the concentration of Na^+ has the potential to cause alterations in the type of water chemistry in the eastern section of the research area. Similar to the TDS, groundwater in cities near the Wei River also contained high levels of Na^+, which may be due to the direction of the groundwater flow and the discharge of the Wei River. NO_3^- was included as the third parameter in the linear regression model. High NO_3^- concentration in drinking water may lead to methemoglobinemia in infants (Adimalla and Li 2019). In this study, most samples fell within the standard limit of NO_3^-, averaging 66.81 mg/L. Moreover, the valley terrace area (including Fufeng, Yangling, Wugong, Xingping, and Xianyang) in the northern Wei River had higher NO_3^- concentrations, while the loess plateau and alluvial plain in the southern part of the Baojixia irrigation district showed lower NO_3^- concentrations (Fig. 9c), suggesting that the pollution in this study area cannot be ignored. The fourth parameter, TH, has a notable ability to explain EWQI and can be utilized to indicate the lithological properties of the strata. Typically, TH of the groundwater is categorized into five levels: very soft (0–75 mg/L), soft (75–150 mg/L), moderately hard (150–300 mg/L), hard (300–450 mg/L) and very hard (> 450 mg/L) (Rezaei and Hassani 2018). The study found that the mean TH of groundwater in the Baojixia irrigation district was 333.17 mg/L, suggesting that the majority of groundwater samples exhibited high water hardness levels. Therefore, water softening was recommended before residential consumption. A significant rise was observed on the TH from the northern to the southern region, with a particular focus on the Wei River terrace such as Yangling, Wugong, and Xingping (Fig. 9d).

In this study, the $EWQI_{min}$ model selected F^- as its fifth parameter. F^- is a crucial component for maintaining human well-being in small amounts, but excessive levels can give rise to non-cancerous hazards, resulting in endemic fluorosis and harm to soft tissues (Duan et al. 2018; Abba et al. 2023). During this study, F^- concentrations ranged from 0.26 to 2.40 mg/L, with an average of 0.86 mg/L, which was close to the acceptable limit of 1 mg/L. The results suggested that the drinking water quality in specific regions within the Baojixia irrigation district might not meet the required standards. Hence, it is imperative to conduct a thorough evaluation of the potential risks to human health in this particular research zone. Chen et al. (2021) have discovered that the majority of groundwater samples containing less than 1.0 mg/L of F^- were primarily located in the southern region of the Wei River and the western region of the Qishui River. These concentrations tended to increase as the direction of river water flow shifted from west to east, aligning with the spatial distribution of F^- observed in this study. As depicted in Fig. 9e, higher concentrations of F^- were observed in the eastern part of the study area, Notably. This is not only related to the dissolution of carbonates but also the mixing of irrigation water along the direction of groundwater flow (Chen et al. 2021; Egbueri et al. 2023). Despite

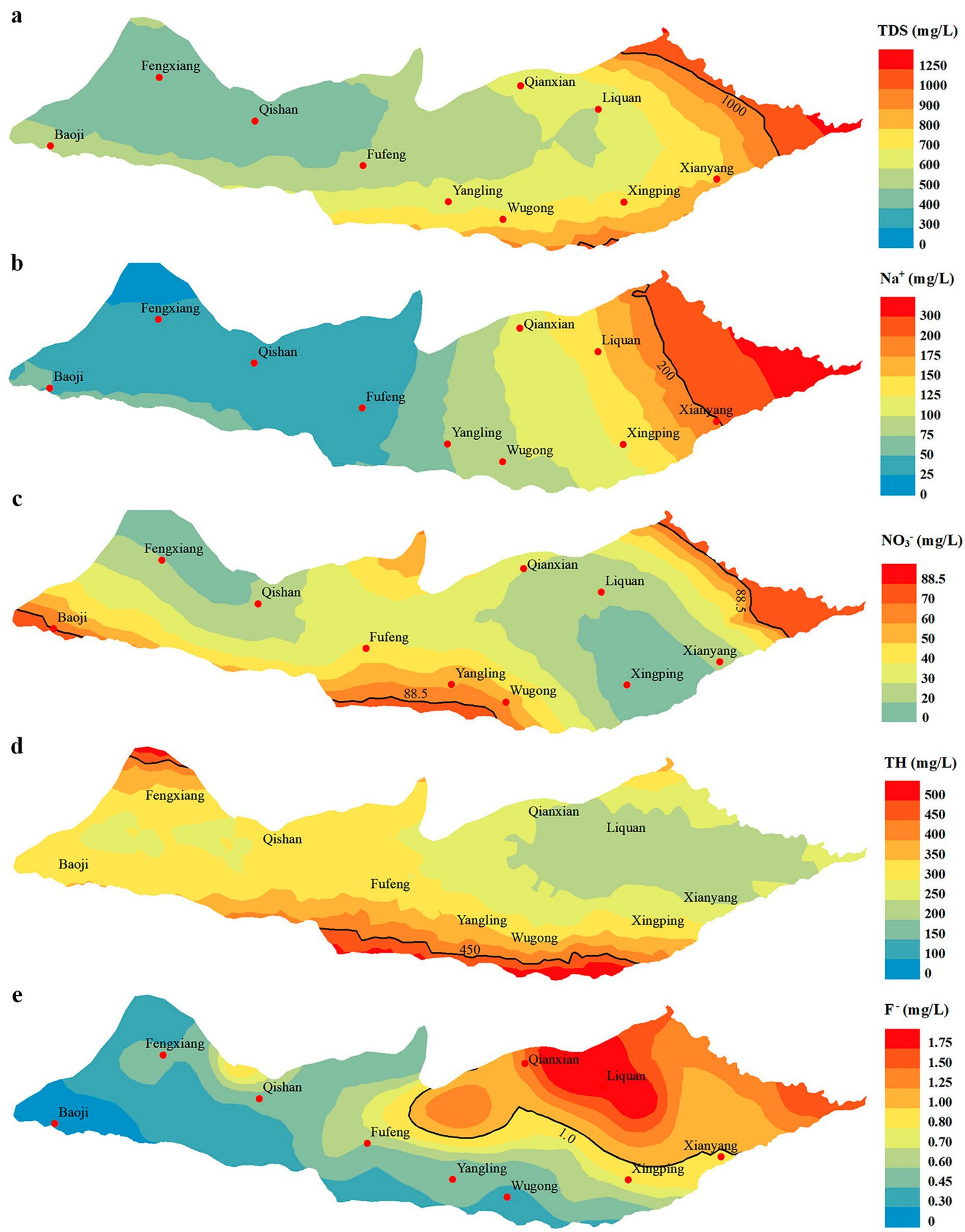


Fig. 9 Spatial distribution of the key parameters selected using the $EWQI_{min}$ model

the higher R^2 values obtained from the linear regression model when selecting COD_{Mn}, the results indicated that the $EWQI_{min}$ model performed worse with COD_{Mn} compared to F^-. This was evident from the higher RMSE and PE values observed (Table 4). Therefore, F^- outperformed COD_{Mn} as a crucial factor in the $EWQI_{min}$ model suggested in this research. Furthermore, these five selected key parameters meet the criteria for convenient measurement since they can be easily accessed through either automated or manual monitoring techniques. This aspect proves advantageous in evaluating the quality of groundwater in the Baojixia irrigation district.

Previous studies conducted in the Guanzhong Basin have provided valuable insights into the selection of these five parameters for the development of the $EWQI_{min}$ model (Wang et al. 2022, 2023b, 2024; Xu et al. 2023a, b; Xie et al. 2023; Nsabimana et al. 2023; Zhang et al. 2022). Ren et al. (2021) analyzed the groundwater quality in the central part of the Guanzhong Basin using the PCA method and identified Na^+, TDS, TH, NO_3^-, and F^- as the key parameters. In addition, Feng et al. (2020) have found that Na^+ was the most critical factor affecting groundwater in the Baojiaxia Irrigation. These results were consistent with the results of the current study, indicating that the five selected parameters had significant impacts on the quality of groundwater in the Baojixia irrigation district.

Future Prospects

Several studies have been carried out on the assessment of groundwater quality using the EWQI model (Wu et al. 2015; Li et al. 2019; Ukah et al. 2020; Yang et al. 2023). Nevertheless, there is a lack of research that specifically addresses the utilization of the $EWQI_{min}$ model for assessing the quality of groundwater. The main highlights of this study were the development of the $EWQI_{min}$ model as the basis for comparing the principal component analysis and multiple linear regression methods using key parameters based on this model, and the selection of the best model for evaluating groundwater quality in the Baojixia irrigation district. The results indicated that the $EWQI_{min}$ model has the ability to fully elucidate the general attributes of groundwater quality and efficiently assess groundwater quality at a comparatively low cost, given the circumstances of controlled operation and a consistent water environment. Therefore, the creation of this model may offer new insights and outlook for assessing groundwater quality. However, there were still some limitations to this study as well. The water quality parameters in this study were analyzed concerning the standards in China. Some specific parameters were not tested in this study, which may limit the further understanding of water quality. In addition, it is worth noting that the performance of the $EWQI_{min}$ model in this study was proposed by considering the weights of the parameters in the evaluation, while the performance of this model without considering the weights of the same key parameters was not clear. Therefore, it's necessary to conduct a comprehensive comparison between the performance of the $EWQI_{min}$ model with and without weights in future studies according to the values of R^2, RMSE, and PE by using the same key parameters.

Conclusions

Groundwater plays a vital role as a resource for human consumption and agricultural irrigation. In this study, the groundwater quality in the Baojixia irrigation district has been evaluated using the $EWQI_{min}$ model, and key parameters influencing the groundwater quality have been selected through the application of PCA and MLR, respectively. Based on the findings of this study, the following conclusions are drawn:

(1) At the time of sampling, the mean values of pH and TH were 8.22 and 333.17 mg/L, respectively, suggesting that the groundwater quality in the Baojixia irrigation district ranged from predominantly slightly to strongly alkaline, and could be classified as hard water. Na^+ and HCO_3^- were the dominant cation and anion in the groundwater, respectively. The hydrochemical facies were predominantly of the HCO_3-Ca·Mg and HCO_3-Na types, which were mainly controlled by rock weathering.
(2) Compared with the $EWQI_{min\text{-}PCA}$ model, the proposed model of $EWQI_{min\text{-}MLR}$ showed better performance for assessing the groundwater quality, consisting of five key parameters, including TDS, Na^+, NO_3^-, TH, and F^-. These key parameters can be easily measured, indicating that the $EWQI_{min\text{-}MLR}$ model is an effective and low-cost method for groundwater evaluation in the Baojixia irrigation district.
(3) Based on the $EWQI_{min}$ classification, the water quality in the Baojixia irrigation district was generally deemed to be "moderate" quality, with the eastern part of the study area exhibiting higher $EWQI_{min}$ values compared to the western part. In general, the eastern part of the study region had poorer water quality than the western part.

Overall, the results showed that the $EWQI_{min}$ model developed in this study was an appropriate and dependable method for evaluating the quality of groundwater in the Baojixia irrigation district. Furthermore, the results can be used as a reference for future studies on the selection of key parameters of the $EWQI_{min}$ model for water quality evaluation.

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