Assessment of karst water quality and analysis of pollution sources with a projection pursuit algorithm in Jinan spring area, China

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ABSTRACT

Karst water is one of the main drinking water sources in North China. The single factor method and projection pursuit algorithm (PPA) are employed to assess the karst water quality of the Baotu spring area in Jinan. The water quality distribution pattern, its causes, and the main groundwater pollution sources are analyzed. The water quality evaluation results of the PPA model are more reliable than those of the single factor method because the PPA model comprehensively considers the weight and correlation of various factors. The water quality of the study area is generally excellent, but the NO3/C0 index content is high. In recent years, the water quality grades have been mainly class II∼class IV. The driving factors of water quality evolution are not only human activities, including artificial recharge, but also natural factors, such as carbonate mineral dissolution. These factors control both the distribution and evolution trend of water quality. Urban nonpoint sources have a significant impact on groundwater quality. Based on the current water quality situation, it is urgent to strengthen protection of the ecological environment in the southern recharge area of the spring region and the water quality control in the western region.

Key words: Jinan spring area, karst water, projection pursuit algorithm, water quality assessment

HIGHLIGHTS

• A projection pursuit algorithm model of regional groundwater quality is established, which has good reliability.
• Anthropogenic activities are the main reason for the deterioration of water quality.
• Urban nonpoint source pollution has the greatest impact on the current water quality.

1. INTRODUCTION

Groundwater is the water resource for almost one third of the people around the world (Ghaffari et al. 2021). It is the world’s largest source of drinking water (Pant et al. 2021) and also is the main water supply source for cities. For example, groundwater supplies 65, 50, and 33% of domestic water, industrial water, and agricultural irrigation water, respectively in northern China (Wu et al. 2020). In some arid and semi-arid regions, groundwater is widely used for drinking water and industrial activities via desalination (Panagopoulos 2020, 2021a). Due to long-term, uncontrolled and irregular exploitation coupled with a long groundwater circulation cycle and slow recovery rate, the groundwater level continues to decline, and the water quality deteriorates, which causes damage to the whole groundwater system (Liu & Ni 2016). In Jinan area, which is famous for its spring water, groundwater is not only the main supply source for industrial and agricultural production but also guarantees continuous gushing of spring water. Scientific and reasonable evaluation of groundwater quality is the key to regional groundwater pollution control and rehabilitation, and rational development and utilization.

To understand the internal mechanism governing the change in chemical components in groundwater, many experts have focused on studying the hydrogeochemical effect of groundwater, and discussed the impact of lithology, landform, runoff velocity, hydrogeological conditions and human activities on the hydrogeochemical characteristics of groundwater (Liu et al. 2019a). They believe that the chemical characteristics of groundwater are determined by the sedimentary environment and are affected by interactions between natural and human factors (Hua et al. 2020; Liu et al. 2020). Groundwater undergoes various physical and chemical interactions with surrounding media during the process of formation and transportation, including dissolution/precipitation, acid-base balance, adsorption/desorption, and oxidation-reduction (Gao et al. 2021). The spring groups in Jinan
experienced four historical evolution periods: perennial gushing period, gushing transition period, attenuation period and artificial regulation periods (Guan et al. 2019). The geochemical characteristics of karst water in the Jinan area are mainly by conventional component trend analysis, the pollution index method, the ion proportion and isotope tracer method and the mathematical statistics method to analyze the spatiotemporal variation in karst groundwater quality (Gao et al. 2019) and changes in pollution components (Huang et al. 2019; Li et al. 2021). In the past ten years, attention has been given to organic pollution (Cheng et al. 2020), Antibiotic contamination (Pan et al. 2021) and artificial regulation and control of the process of source supplementation (Li 2019), and many achievements have been made. However, to understand water quality evolution, more emphasis is placed on the impact of human activities, while an in-depth exploration of the internal causes of hydrogeology and a discussion of the spatiotemporal differences in karst groundwater quality are lacking.

Due to the complex, high-dimensional and nonlinear characteristics of water quality assessments, when water quality data are numerous and have many parameters, it is difficult to distinguish the influence of natural factors, such as geochemical processes, from human factors, such as industrial and agricultural activities, on groundwater quality by conventional methods. Intelligent optimization algorithms are widely employed in groundwater quality assessments. Commonly utilized methods include the fuzzy artificial neural network, health risk assessment methods. These methods simplify the problem-solving to a certain extent, but some shortcomings still exist: the parameters of the fuzzy artificial neural network method are difficult to set; the convergence speed is slow; the stability is poor; it is easy to succumb to local minimization; and the resolution is low (Liu et al. 2019b). The health risk assessment method considers only the harm of pollutants to the human body as the measurement standard (Liu et al. 2018). The projection pursuit evaluation model is completely data-driven and avoids the interference of subjective factors. This model projects high-dimensional data into low-dimensional space and analyzes the characteristics of high-dimensional data according to the projected eigenvalues, thereby reflecting the structure and characteristics of high-dimensional data in low-dimensional space to solve the high-dimensional problem (Liu et al. 2019b).

On the basis of previous studies, this paper uses the single factor method and Projection Pursuit Algorithm (PPA) to evaluate the diachronic change in the karst water quality grade in spring areas; analyzes the spatial variation and causes of water quality; and explains the internal mechanism of groundwater quality change according to the possible hydrogeochemical processes in different regions. The absolute principal component score-multiple linear regression receptor (APCS-MLR) model (Hou et al. 2021) is employed to determine the contribution rate of each factor that influences the index and to quantitatively analyze the degree of influence of pollution sources on the important physical and chemical factors of water, which can provide a scientific basis for the control and repair of regional groundwater pollution and rational development and utilization.

2. STUDY AREA

Jinan is a city in midwestern Shandong Province, China, its geographical location is 116°11’E ~ 117°44’E and 36°02’N ~ 37°31’N. Controlled by the warm temperate continental monsoon climate, its annual average temperature and precipitation were 14.3 °C and 641.68 mm respectively (1956–2012). Moreover, precipitation is mainly concentrated during the months of June to September, which accounts for 75% of the total annual precipitation (Sun et al. 2020).

Mountains and plains are distributed in the South and north of Jinan spring area respectively. The area is a monoclinic structural geological with a slight northward tilt and exhibits a typical karst development area in northern China that encompasses 1114 km² (Figure 1) (Meng et al. 2020). From old to new and from south to north, the strata in the spring area successively include the Neoarchean Taishan Group and early Paleozoic Cambrian, Ordovician, late Paleozoic-Carboniferous, Permian, Neogene and Quaternary strata (Yang et al. 2016). Among these strata, the Cambrian-Ordovician carbonate rocks are the main water-bearing rocks in the Jinan spring area, with a total thickness of nearly 1000 m. From south to north, the spring area is divided into indirect recharge areas, direct recharge and collection areas and discharge areas. Karst landforms are well developed in the southern mountainous area, and abundant karst groundwater is formed after a large amount of atmospheric precipitation accumulates. In the north, the approximate water-blocking boundary is formed by weak permeable igneous rock intrusion, and the igneous rocks interpenetrate the limestone layers, so the groundwater pushes out along the tectonic layers to form springs (Guan et al. 2019). The main source of karst water supply is precipitation
infiltration followed by surface water. The anthropogenic over exploitation of karst water has resulted in intermittent disconnections of spring water in the northern spring area for a long time. After 2001, Jinan gradually reduced groundwater exploitation by increasing the water supply from Yuqing Lake and the Queshan Reservoir and implemented recharge in the Yufu River to restore the famous spring (Li et al. 2017). A series of measures causes the regional surface water and groundwater hydraulics to be in close contact, and the karst aquifer is easily contaminated by surface water (Li 2019).

3. MATERIALS & METHODS

3.1. Data sources

The groundwater quality data comes from 320 groups of groundwater samples, which collected from 2012 to 2019. The water quality monitoring points (refer to Figure 1) are distributed in the direct recharge, indirect recharge and discharge areas. The samples were stored in polythene bottles, which pre-cleaned with 1 N hydrochloric acid and rinsed 3 times with distilled water. Before water sampling, all the polythene containers were cleaned and rinsed thoroughly with water samples to be analyzed. After the flow and quality of water reach a stable state, collected samples, sealed the bottle mouth and record the sample number, sampling time, place and other information immediately. Then transport it back to the laboratory, and complete analysis within 5 days. The Electrical Conductivity (EC) and pH were measured by AquaTROLL600 multi parameter water quality detector in field. In the laboratory, the water samples were analyzed for the major anions i.e. bicarbonate, chloride, sulphate etc. and cations i.e. calcium, magnesium, sodium, potassium etc. Water analysis was done using methods for the examinations of water and waste water (APHA 1998). Total hardness (TH) as CaCO3 and calcium (Ca2+) were analyzed titrimetrically, using standard EDTA. Chloride (Cl−) was determined titrimetrically by standard AgNO3 titration. The content of sodium (Na+) and potassium (K+) in groundwater was estimated using Shimadzu atomic absorption spectrophotometer AA7000 graphite furnace method, and the test accuracy is 0.5 μg/L. In order to ensure the accuracy of the test results, the samples were rechecked by ICP-MS (Inductively coupled plasma mass spectrometry). Finally, 307 groups of groundwater quality monitoring data are selected (including 37 groups in 2012, 34 groups in 2013, 40 groups in 2014, 44 groups in 2015, 44 groups in 2016, 44 groups in 2017, 44 groups in 2018 and 20 groups in 2019). The statistical results of the main ion components are shown in Table 1.

3.2. Single factor index method of groundwater quality evaluation

In the newly issued groundwater quality standard (GB/T 14848-2017), the single factor index method is recommended to evaluate water quality. This method is to evaluate each pollution factor separately (Liu 2014), and take the worst result as the final water quality result of the water sample. Considering the ‘Standard for groundwater quality’ (GB/T 14848-2017), eight representative indicators are selected as evaluation factors of groundwater quality, and the water quality grade is divided into five categories. The standard index concentration of each grade is listed in Table 2.
tion, each sample value with n-dimensional data can be projected in this direction, and the high-dimensional data

\[ z \sim z_{\text{up}} - z_{\text{down}} \]

where \( z_{\text{up}} \) and \( z_{\text{down}} \) are the upper limit and lower limit, respectively, of the b-th indicator in the evaluation standard sample set, respectively. \( z(i, j) \) is the data sample value after standardization, and \( z^* (i, j) \) is the data sample value after standardization, \( z_{\text{max}}(j) \) and \( z_{\text{min}}(j) \) are the maximum value and minimum value of the b-th indicator in the evaluation standard sample set, respectively. \( e \) is the data sample value in the n-dimensional data set.

\[ z^* (i, j) = \frac{z(i, j) - z_{\text{min}}(j)}{z_{\text{max}}(j) - z_{\text{min}}(j)} \]

Moderation index as follows:

\[ z^* (i, j) = 1 - \frac{0.5(z_{\text{up}}(j) + z_{\text{down}}(j)) - z(i, j)}{z_{\text{max}}(j) - z_{\text{min}}(j)} \]

Secondly: Construction of projection index function. Let \( e = [e(1), e(2), \ldots, e(n)] \) be the unit vector in any direction, each sample value with n-dimensional data can be projected in this direction, and the high-dimensional data

\[ z = \sum_{i=1}^{n} e(i) z(i) \]

Firstly: Standardize the sample index data. Let \( \{z(i, j)\}_{i=1, j=1}^{m,n} \) as the j-th index of the i-th sample, m as the number of samples and n as the number of indicators. In order to eliminate the influence of different index dimensions on the sample data, the original data are normalized:

\[ z(i, j) = \frac{z(i, j) - z_{\text{min}}(j)}{z_{\text{max}}(j) - z_{\text{min}}(j)} \]

\[ z^*(i, j) = \frac{z(i, j) - z_{\text{min}}(j)}{z_{\text{max}}(j) - z_{\text{min}}(j)} \]

For the smaller, the better index as follows:

\[ \tilde{z}(i, j) = \frac{z_{\text{max}}(j) - z(i, j)}{z_{\text{max}}(j) - z_{\text{min}}(j)} \]

where \( z_{\text{min}}(j) \) and \( z_{\text{max}}(j) \) are the maximum value and minimum value of the b-th indicator in the evaluation standard sample set, respectively. The projection value makes the projection index function reach the optimal, and evaluate it according to the projection value (Liu et al. 2018, 2019b) which is divided into the following four steps:

1. **Firstly:** Standardize the sample index data. Let \( \{z(i, j)\}_{i=1, j=1}^{m,n} \) as the j-th index of the i-th sample, m as the number of samples and n as the number of indicators. In order to eliminate the influence of different index dimensions on the sample data, the original data are normalized:

\[ z(i, j) = \frac{z(i, j) - z_{\text{min}}(j)}{z_{\text{max}}(j) - z_{\text{min}}(j)} \]

2. **Secondly:** Construction of projection index function. Let \( e = [e(1), e(2), \ldots, e(n)] \) be the unit vector in any direction, each sample value with n-dimensional data can be projected in this direction, and the high-dimensional data

**Table 2 | Standard for groundwater quality**

| Grade | pH   | Na⁺/mg·L⁻¹ | Cl⁻/mg·L⁻¹ | SO₄²⁻/mg·L⁻¹ | F⁻/mg·L⁻¹ | TH/µS·cm⁻¹ | CO₂⁺max/mg·L⁻¹ | NO₂⁻/mg·L⁻¹ | TDS/mg·L⁻¹ |
|-------|------|------------|------------|--------------|-----------|------------|-----------------|-------------|-----------|
| I     | 6.5 ~ 8.5 | ≤ 100 | ≤ 50 | ≤ 50 | ≤ 1.0 | ≤ 150 | ≤ 1 | ≤ 2.0 |           |
| II    | 6.5 ~ 8.5 | ≤ 150 | ≤ 150 | ≤ 150 | ≤ 1.0 | ≤ 300 | ≤ 2 | ≤ 5.0 |           |
| III   | 6.5 ~ 8.5 | ≤ 200 | ≤ 250 | ≤ 250 | ≤ 1.0 | ≤ 450 | ≤ 3 | ≤ 20.0 |           |
| IV    | 5.5 ~ 6.5, 8.5 ~ 9 | ≤ 400 | ≤ 350 | ≤ 350 | ≤ 2.0 | ≤ 650 | ≤ 10 | ≤ 30.0 |           |
| V     | < 5.5, > 9 | > 400 | > 350 | > 350 | > 2.0 | > 650 | > 10 | > 30.0 |           |

**3.3. Projection pursuit algorithm (PPA) model of groundwater quality evaluation**

The basic principle of the PPA model is to project the high-dimensional data onto the low-dimensional space, use the projection index function to describe the projection value, expose the possibility of the original system to comprehensively evaluate a classiﬁcation and sorting structure, and ﬁnd the projection value that makes the projection index function reach the optimal, and evaluate it according to the projection value (Liu et al. 2018, 2019b) which is divided into the following four steps:

1. **Firstly:** Standardize the sample index data. Let \( \{z(i, j)\}_{i=1, j=1}^{m,n} \) as the j-th index of the i-th sample, m as the number of samples and n as the number of indicators. In order to eliminate the influence of different index dimensions on the sample data, the original data are normalized:

\[ z(i, j) = \frac{z(i, j) - z_{\text{min}}(j)}{z_{\text{max}}(j) - z_{\text{min}}(j)} \]

2. **Secondly:** Construction of projection index function. Let \( e = [e(1), e(2), \ldots, e(n)] \) be the unit vector in any direction, each sample value with n-dimensional data can be projected in this direction, and the high-dimensional data

**Table 1 | Statistics of main ion concentration of 307 water samples in different years in the study area**

| Parameters | Indirect recharging area | Direct recharging area | Discharging area |
|------------|--------------------------|------------------------|-----------------|
| pH         | Min. | Max. | Mean | Min. | Max. | Mean | Min. | Max. | Mean |
| K⁺/mg·L⁻¹  | 0.38 | 42.65 | 5.1 | 0.13 | 57.59 | 6.02 | 0.35 | 42.87 | 2.41 |
| Na⁺/mg·L⁻¹ | 3.33 | 112.87 | 19.32 | 0.67 | 208.85 | 40.04 | 9.14 | 118.95 | 25.14 |
| Ca²⁺/mg·L⁻¹ | 46.34 | 227.18 | 90.07 | 16.6 | 214.03 | 119.45 | 43.89 | 202.4 | 109.46 |
| Mg²⁺/mg·L⁻¹ | 0.09 | 51.32 | 13.54 | 2.37 | 36.58 | 16.61 | 7.95 | 148.4 | 24.99 |
| Cl⁻/mg·L⁻¹  | 0.1 | 135.07 | 21 | 0.2 | 186.48 | 49.16 | 0.7 | 97.72 | 52.81 |
| SO₄²⁻/mg·L⁻¹ | 2.84 | 92.28 | 69.28 | 6.73 | 112.15 | 92.09 | 11.72 | 164.45 | 100.9 |
| HCO₃⁻/mg·L⁻¹ | 0.25 | 346.35 | 163.65 | 1.65 | 479.17 | 237.72 | 1.75 | 362.34 | 254.43 |
| F⁻/mg·L⁻¹     | 0.1 | 0.5 | 0.14 | 0 | 0.65 | 0.15 | 0.1 | 0.39 | 0.17 |
| NO₂⁻/mg·L⁻¹  | 0.1 | 135.07 | 21 | 0.2 | 186.48 | 49.16 | 0.7 | 97.72 | 52.81 |
| TDS/mg·L⁻¹   | 321.33 | 740 | 279.54 | 295.34 | 870 | 345.32 | 387.72 | 600 | 364.69 |
can be transformed into 1-dimensional projection value \( f(i) \) through dimension reduction processing, and \( e(j) \) is the weight of the \( j \)-th evaluation index. The formula is:

\[
f(i) = \sum_{j=1}^{n} e(j)z'(i, j) \quad i = 1, 2, \ldots, m
\]  

(4)

The projection objective function \( Q(e) \) can be expressed as:

\[
Q(e) = S(f)D(f)
\]

(5)

\[
S(f) = \sqrt{\frac{\sum_{i=1}^{m} (f(i) - \bar{f}(i))^2}{m - 1}}
\]

(6)

\[
D(f) = \sum_{i=1}^{m} \sum_{j=1}^{n} (R - d(i, j)) \cdot U(R - d(i, j))
\]

(7)

where \( \bar{f}(i) \) is the average value of the projection value in the projection direction, and \( R \) is the window radius of the local density; \( d(i, j) = |f(i) - f(j)| \); \( U \) is a unit step function. When \( R \cdot d(i, j) \geq 0 \), \( U \) is 1, otherwise it is 0.

Thirdly: The optimization algorithm is used to search the best projection direction. The optimal projection direction of the evaluation index, that is, the optimal weight value, can be obtained by optimizing Equation (7).

\[
\begin{align*}
\text{Max: } & Q(e) = S(f) \cdot D(f) \\
\text{s.t. } & \sum_{j=1}^{n} f^2(j) = 1
\end{align*}
\]

(8)

Finally: Divide the evaluation grade according to the optimal weight value. Draw the scatter diagram of projection value \( f \) – standard level \( y \) to obtain the level of each sample.

### 3.4. Ameliorative moth-flame optimization algorithm

The solution of projection function \( Q(e) \) belongs to a complex nonlinear function solving process. In the process of optimization, to avoid the lack of robustness of traditional optimization algorithms and the phenomenon of ‘premature convergence’, the Ameliorative Moth-Flame Optimization algorithm (AMFO) (Liu et al. 2019b) is introduced to solve the optimal projection direction. Tian et al. proposed an AMFO algorithm based on the Kent chaotic dynamic inertia weight (Tian et al. 2019). Unlike the Moth-Flame Optimization (MFO), the AMFO adds the dynamic inertia weight and chaotic map optimization MFO algorithm. In the AMFO algorithm, the Kent chaotic map search strategy was used to achieve the original optimal solution jump out of the local optimum based on the fitness value and the number of iterations.

#### 3.4.1. Generation of the initial moth population

In the MFO algorithm (Almazok & Bilgehan 2020; Zhao et al. 2020), the moth population (the candidate solution of the optimization problem) is recorded as \( M \) (Equation (8)), the individual fitness value is stored in the \( OM \) matrix (Equation (10)), the flame (the best position obtained in the current iteration) is recorded as \( F \) (Equation (11)), and its fitness value is stored in the \( OF \) matrix (Equation (13)).

\[
M = [m_1, m_2, \ldots, m_d]^T
\]

(8)

\[
m_i = [m_{i,1}, m_{i,2}, \ldots, m_{i,d}]^T
\]

(9)

\[
OM = [OM_1, OM_2, \ldots, OM_n]^T
\]

(10)

\[
F = [f_1, f_2, \ldots, f_d]^T
\]

(11)

\[
f_i = [f_{i,1}, f_{i,2}, \ldots, f_{i,d}]^T
\]

(12)

\[
OF = [OF_1, OF_2, \ldots, OF_n]^T
\]

(13)

where \( n \) is the number of moths and \( d \) is the dimension of the optimization problem.
3.4.2. Moth position update

According to the behavior characteristics of moths in nature, the moth updates the position and the number of optimal solutions according to the moving track of Equations (14) and (15):

\[
S(M_i, F_j) = D_i \times e^{bt} \times \cos (2\pi t) + F_j
\]  

(14)

where \(S(M_i, F_j)\) is the updated moth position; \(D_i\) represents the distance between the \(i\)-th moth for the \(j\)-th flame, \(D_i = |F_j - M_i|\); \(b\) is a constant of the shape of the logarithmic spiral, and \(t\) is a random number in \([-1, 1]\).

\[
no_{\text{flame}} = \text{round}\left(\frac{N - I \times N - 1}{T}\right)
\]  

(15)

where \(I\) is the present number of the iteration, \(N\) shows the maximum value of the flames, and \(T\) is the maximum number of iterations.

3.4.3. AMFO algorithm

The optimal solution \(M_i\) is mapped into the domain \([0,1]\) by Equation (16). Using the Kent iteration, the chaotic sequence \(Z_n\) is generated, where \((n = 1, 2, \ldots)\), and a new individual location \(U_k\) is obtained by Equation (17):

\[
z_0 = \frac{M_i - M_{\text{min}}}{M_{\text{max}} - M_{\text{min}}}
\]  

(16)

\[
U_k = M_i + \frac{M_{\text{max}} - M_{\text{min}}}{2} \times (2Z_k - 1)
\]  

(17)

In the AMFO algorithm, the weight value is determined according to the dynamic inertia weight strategy \(w\), as in Equation (18); an improved position update Equation (19) can then be obtained:

\[
w_{ij} = \frac{\exp (f(j) - \mu)}{2.4 \times \exp (-f(j)/\mu)^{iter}}
\]  

(18)

\[
S(M_i, F_j) = w_{ij} \times D_i \times e^{bt} \times \cos (2\pi t) + (1 - w_{ij}) \times F_j
\]  

(19)

where, \(\mu\) is the average fitness value of the first optimization process; \(f(j)\) is the fitness value of the \(j\)-th moth; \(\text{iter}\) indicates the current number of iterations.

The specific implementation process of the algorithm is as follows:

a. Initialization of algorithm parameters, such as the number of moths \(n\), dimension \(d\), and maximum number of iterations \(T\);

b. Population initialization according to Equation (8);

c. Calculate the fitness value of artificial moths and artificial flames;

d. Update the first flame \(F1\) according to the improved method;

e. Update the number of flames according to Equation (15);

f. Update the dynamic inertia weights according to Equation (18);

g. Update the position of the moth according to Equation (19);

h. If the termination condition is met, the algorithm ends and the optimal solution is obtained; otherwise, it returns to step c.

3.5. APCS-MLR source analysis model

The first step of APCS-MLR model (Hou et al. 2021) is to extract the principal components of water quality indicators by principal component analysis/factor analysis (PCA/FA) method to further identify pollution sources. The variance variation of the whole data set is explained by several principal components selected, and the pollution contribution of each pollution source is calculated (Qin et al. 2020; Zhang et al. 2020b). The contribution
rate of each component to the variable concentration can be described as follows:

\[ J_i = b_{0i} + \sum_{q=1}^{n} (APCS_q \cdot b_{qi}) \]  

(20)

\[ b_{0i} \] is the multiple regression constant term of pollutant \( i \); \( b_{qi} \) is the multiple regression coefficient of source \( q \) of pollutant \( i \); and \( APCS_q \) is the scale value of the sample rotation factor \( q \). \( APCS_q \cdot b_{qi} \) represents the contribution of source \( q \) to \( J_i \).

4. RESULTS AND DISCUSSION

4.1. Single factor evaluation results of water quality

The single factor water quality evaluation method is selected to evaluate the groundwater quality in the spring area from 2012 to 2019, and the spatial distribution map of groundwater quality is constructed (Figure 3). According to all the evaluation results, the groundwater quality grade in the spring area is mostly class IV and class V. Figure 4 shows the different components in groundwater from 2012 to 2019 that were greater than the standard. Except for nitrate and total hardness, other indicators fell within the class III water standard. NO\(_3\) exceeded the standard of class III water quality in GB/T 14848-2017 in all years, and the nitrate index exceeded the standard by more than 60%; thus, the water quality assessment results of most regions remain in the class range IV \( \sim \) V. In the single factor evaluation, NO\(_3\) is the pollution index with the greatest impact on water quality.

4.2. PPA model results of water quality

4.2.1. Training of the projection value to the hierarchical value function

Take the five standard grade intervals of class I \( \sim \) V water obtained in Table 1 as the initial projection direction, that is, the 5-Dimensional unit vector. After normalization, select the local density window width is \( R = d_{\text{max}}/4 \), where \( r_{\text{max}} \) is the maximum value of \( d(i, j) \) (Liu et al. 2018), and construct the projection index function. The moth fire optimization algorithm is used to solve the objective function, and the projection direction \( e = [0.0900 0.1352 0.1455 0.3078 0.1157 0.8269 0.1506 0.3788] \). The value of the projection direction indicates the relative importance of each index to groundwater quality, and the order of the relative importance of each index is obtained.
as follows: COD$_{Mn}$ > NO$_3^-$ > SO$_4^{2-}$ > Cl$^-$ > Na$^+$ > total hardness (TH) > pH > F$^-$. The best projection value $f = [0.9537 \ 0.8595 \ 0.7178 \ 0.5721 \ 0.3781]$ is calculated according to the best projection direction $e$.

By drawing the scatter diagram of projection value ($f$) ~ standard grade ($y$) and curve fitting, the correlation between projection value and water quality grade can be obtained, as shown in Figure 5, and then the classification standard of groundwater quality index of each grade can be obtained. The correlation coefficient of the fitting function $R^2 = 0.9992$. It can be seen that the constructed projection pursuit evaluation model of groundwater quality grade has high accuracy. The classification standard of the comprehensive evaluation of water quality is shown in Table 3.
Figure 4 | The number of different pollutants exceeding the standard rate from 2012 to 2019.

Figure 5 | Relationship between projection values and standard grade.
The measured data of water quality in different years are normalized and brought into the PPA model to obtain the sample projection value \( f \) and standard grade \( y \). According to the groundwater quality evaluation and classification standard (as shown in Table 3), the spatial distribution of groundwater quality grades can be obtained (Figure 6).

In terms of spatial distribution, the class I and II groundwater are mainly concentrated in the pressure-bearing area covered by igneous rocks in the east, while the class III and IV groundwater are distributed in the area that is directly covered by Quaternary sediments in the central and western regions, and the water quality in the northeastern spring area is the worst. In the eastern part of the spring region, along the groundwater flow direction, the water quality grade gradually decreases from the southern to the northern, and there is no obvious law of water quality change in the central and western regions. Igneous rocks interpenetrate between the Quaternary unconsolidated strata and limestone aquifers, which weakens the hydraulic connection between the two aquifers and improves the protective effects of the karst aquifer in the eastern part of the spring area so that the groundwater is not easily affected by the outside world. The main source of infiltration recharge in the eastern region is atmospheric precipitation on the exposed limestone area in the south, and the recharge mode is relatively simple. Moreover, the water quality in the southern recharge area can reach above class II, which improves the whole water quality in the eastern part of the spring area. There are many industrial and mining enterprises in the northeastern part of the spring area, and urban construction is developing rapidly. Years of artificial mining reduced the groundwater level in Jinan from 30 m in the 1950 and 1960s to 27 m in the middle of 1980s (Xing 2006). The upper phreatic water passes through the igneous rock aquitard to supply the lower karst resulting in the deterioration of water quality. For example, the water quality of Huaneng Power Plant in the Northeast has deteriorated significantly in recent years. Since 2006, the salinity of groundwater has been maintained at about 900 mg/L, the mass concentration of NO\(_3^-\) has been maintained at about 900 mg/L, and the mass concentration of SO\(_4^{2-}\) is 100 mg/L ~ 150 mg/L (Sun et al. 2018). The infiltration of pollutants such as industrial wastewater and domestic sewage has gradually worsened the karst water quality in the northeast of the spring area (Xing 2006). In the western part of the spring area, the Quaternary aquifer directly covers the limestone in the piedmont alluvial plain which formed by the Yufu river and Beidasha river, but a good aquiclude is lacking (Sun et al. 2018). The river on the surface and Quaternary pore water supply groundwater directly by leakage. The water quality of the recharge source directly affects the groundwater quality grade in the western spring area. In addition, groundwater is discharged through several water sources in the western area and spring groups in the middle of the spring area, and circulation and alteration occur quickly. Due to the influence of various recharge sources and water circulation rates, the groundwater quality in the central and western regions has changed greatly, and class III, IV and V water are appeared. In contrast, the water quality in the pressure-bearing area covered by igneous rocks in the spring area is generally better than that Quaternary direct coverage area.

According to the groundwater quality assessment results in different years, the frequency of each water quality grade in the total study area was calculated (Figure 7). The groundwater quality grade in the study area is mainly class II ~ class IV. class I water only appeared in 2012, 2015 and 2017, and the proportion is less than 5%; The proportion of class II and class III water is expanding, the total proportion of the former increased from 18.9% in 2012 to 98% in 2018; After 2013, the total proportion of class II and class III water was more than 60%, the proportion of class IV and class V water decreased significantly, and class V water appeared occasionally.

### 4.3. Comparative analysis of the evaluation results

The single factor evaluation results reveal that some indicators of groundwater in the study area exceed the standard and the exceeding indicators are NO\(_3^-\), COD\(_{Mo}\), TH (total hardness), and Na\(^+\). COD\(_{Mo}\) and Na\(^+\) exceeded the standard at only one sampling point. Therefore, the main pollution factors in the study area were NO\(_3^-\) and TH. The single factor evaluation takes the worst result of all evaluation indexes as the final evaluation result. This method can accurately detect the main pollutants in regional groundwater, highlight the impact of excessive

| Grade | I | II | III | IV | V | Worse than V |
|-------|---|----|-----|----|---|--------------|
| Fitting values | [0,0.99] | (0.99,2.03] | (2.03,2.94] | (2.94,4.05] | (4.05,4.98] | > 4.98 |
index factors on water quality. However, the single factor evaluation method has one sidedness and limitations, it implements ‘one ballot veto’ or ‘one-size-fits-all’ for all indicators affecting water environmental quality, ignores the contribution of other factors to water quality. According to the evaluation results, although other water quality indexes are within the class III water standard, only one index exceeds the standard (NO₃⁻), the water quality evaluation results are class IV ~ class V. So, the single factor evaluation method lacks effective classification of water pollution degree.

Different from the single factor index method, the PPA model comprehensively considered the weight of each factor and the correlation among the factors, found the best projection direction among a variety of pollutants, reduced the strong interference of a single inferior index to the water quality evaluation results effectively, and
the problem of incompatibility and fuzziness of various indexes in the process of water quality evaluation is well solved.

The AMFO algorithm further ensured the objectivity and accuracy of the evaluation results, avoided the subjectivity and one-sidedness of the calculation process. Therefore, the evaluation results of AMFO-PPA model are more reliable than those of single factor evaluation model.

4.4. Analysis on driving factors of water quality change

4.4.1. Evolution of the groundwater environment

4.4.1.1. Hydrochemical characteristics and hydrochemical types. According to the statistical results of the main ions in Table 1, the concentration of Ca$^{2+}$ in the water samples is 16.60 mg/L ~ 227.18 mg/L, which is the main cation; Na$^+$ and Mg$^{2+}$ are secondary cations in the water samples; and the average value of K$^+$ is 5.36 mg/L, with the lowest content. The contents of Na$^+$, Ca$^{2+}$, Mg$^{2+}$ and other cations in groundwater increase along the groundwater flow direction. In addition to NO$_3^-$ or CO$_2^-$, other ions show an increasing trend along the groundwater flow. Therefore, the pollutants in the karst water in the recharge area tend to accumulate in the downstream discharge area, resulting in a gradual increase in the concentration and deterioration in the water quality. In addition, as a comprehensive hydrochemical parameter, total dissolved solids (TDS) can be utilized to reflect the groundwater quality (Zhang et al. 2020a). The concentration of TDS in the collected samples is less than 1 g/L, so it can be seen that the groundwater in the study area is low mineralized water. In recent years, the TDS values of groundwater ranged from 295.34 mg/L to 870 mg/L. The average TDS values of the indirect recharge area, direct recharge area and discharge area were 279.54 mg/L, 345.32 mg/L and 364.69 mg/L, respectively. In summary, the distribution characteristics of ion contents reveal that the water quality in the spring area gradually deteriorates along the groundwater flow direction, which is particularly distinct in the water quality evaluation results in the eastern spring area. The central and western regions may be disturbed by other factors, so that the water quality grade evaluation results do not show obvious regularity.

According to the Shukalev classification method, the groundwater hydrochemical types in the spring area are mainly HCO$_3$-Ca type and HCO$_3$-SO$_4$-Ca type; the Ordovician karst hydrochemical type in the direct recharge area is mainly HCO$_3$-SO$_4$-Ca type; the Cambrian karst hydrochemical type in the indirect recharge area is mainly HCO$_3$-Ca type. From the spring recharge area to the discharge area, the hydrochemical type of
groundwater gradually transforms from HCO₃-Ca type to HCO₃-SO₄-Ca type. With the lengthening of migration path and the strengthening of water rock interaction, the hydrochemical type is more complex.

Affected by the leakage of the Yufu River, the hydrochemical types in the surrounding areas are complex and diverse and include HCO₃-SO₄-Ca type water.

In the spring discharge area, the HCO₃-SO₄-Ca type groundwater only in Baotu spring and Heihu spring are, and the hydrochemical type of other springs is HCO₃-Ca type.

4.4.1.2. Water rock interaction processes. According to the hydrogeological conditions, the main carbonate minerals that affect the chemical composition of groundwater are calcite, dolomite and gypsum. The main chemical reaction equations are expressed as follows:

- Calcite dissolution: \( \text{CaCO}_3 + \text{CO}_2 + \text{H}_2\text{O} = \text{Ca}^{2+} + 2\text{HCO}_3^- \) (21)
- Gypsum dissolution: \( \text{CaSO}_4 \cdot 2\text{H}_2\text{O} = \text{Ca}^{2+} + \text{SO}_4^{2-} + 2\text{H}_2\text{O} \) (22)
- Dolomite dissolution (dedolomitization): \( \text{CaMg}((\text{CO}_3)_2 + \text{Ca}^{2+} = \text{Mg}^{2+} + \text{CaCO}_3 \) (23)

To further understand the hydrochemical evolution of regional groundwater and the influence of the water-rock interaction process on water quality change, a diagram that shows the ratio of the main ion relationship in each water function division is constructed according to the hydrochemical characteristics from 2012 to 2019 (Figure 8). If the water quality change is caused by the dissolution of minerals in the aquifer, the synchronous growth of \( \text{Ca}^{2+} \) and \( \text{SO}_4^{2-} \) indicates that insoluble microcrystalline gypsum is dissolving, while the synchronous growth of \( \text{Na}^+ \) and \( \text{Cl}^- \) indicates that soluble microcrystalline salt is dissolving.

Figure 8(a) shows the main anion relationship in groundwater: most of the points are located on the upper side of the 1:1 straight line, indicating that the main role of groundwater hydrochemical formation is the dissolution of carbonate minerals, and the point under the 1:1 straight line may be accompanied by evaporation (Hong et al. 2016), which is related to the increase in \( \text{SO}_4^{2-} \) and \( \text{Cl}^- \) contents in the water body caused by other reasons. In Figure 8(b), the relationship between \( \text{Na}^+ \) and \( \text{Cl}^- \) is not completely synchronous. In all groundwater samples, the contents of \( \text{Na}^+ \) and \( \text{Cl}^- \) distributed along the 1:1 trend line only in a few samples, and most samples are above the 1:1 trend line, indicating that only a few sampling points produce water quality changes due to the dissolution of halite, and most of the points that deviate from the 1:1 trend line may also undergo cation exchange, resulting in high \( \text{Na}^+ \) content (Zhang et al. 2020a). In Figure 8(c), the ratios of \( \text{Ca}^{2+} \) to \( \text{SO}_4^{2-} \) at almost all sampling points are located above the unit line, indicating that nonwater-rock interactions produce \( \text{Ca}^{2+} \) in karst water, and other ion exchange processes, in addition to gypsum dissolution, exist (Abu-Alnaeem et al. 2018). The data in Figure 8(b) and 8(c) deviate from the unit hydrograph, indicating the lack of evidence for the simple dissolution of halite and gypsum (Gao et al. 2020) and the mixing of other water bodies. The plot of \( \text{Ca}^{2+} + \text{Mg}^{2+} + \text{SO}_4^{2-} + \text{HCO}_3^- \) was used to examine the effects of sulfate and carbonate minerals distribution in system. The sample points along the 1:1 line are recognized to weathering of sulfate and carbonate minerals. Reverse ion exchange processes cause the points above the 1:1 line. The data points below the aquiline are considered because of sulfates and carbonates dissolution. The Figure 8(d) showed that a few points fall around the 1:1 line. Some points were above the aquiline, indicating the impacts of cation exchange and weathering of silicate minerals. The other points dropped below the line and indicated the impact of the dissolution of sulfate and carbonate minerals (Lanjwani et al. 2021).

To understand the influence of the dissolution process of minerals other than gypsum on karst hydrochemistry, the amounts of ‘nongypsum source calcium’ and ‘noncarbonate rock calcium’ are calculated respectively. Assuming that all \( \text{SO}_4^{2-} \) in karst water is derived from the dissolution of gypsum, ‘nongypsum source calcium’ can be obtained from the total \( \text{Ca}^{2+} \) minus the calcium in gypsum that is equivalent to \( \text{SO}_4^{2-} \), which is expressed as \( \text{Ca}^{2+} \cdot \text{SO}_4^{2-} \) (Wang et al. 2017), ‘noncarbonate rock calcium’ can be expressed as \( \text{Ca}^{2+} \cdot 0.33\text{HCO}_3^- \), with a coefficient of 0.33, which is obtained from the following reaction chemistry calculation (Yang et al. 2019):

\[
\text{CaCO}_3 + \text{CaMg}((\text{CO}_3)_2 + 3\text{CO}_2 + 3\text{H}_2\text{O} = 2\text{Ca}^{2+} + \text{Mg}^{2+} + 6\text{HCO}_3^- \quad (24)
\]

The 1:2 relationship line and 1:4 relationship line in Figure 8(e) represent the dissolution equilibrium of calcite and dolomite, respectively. Most of the samples are distributed between the 1:4 equilibrium line and the 1:2
equilibrium line and deviate to the 1:2 equilibrium line, which shows that Ca\(^{2+}\) and HCO\(_3^-\) in karst water mainly come from the dissolution of calcite, followed by the dissolution of dolomite (Yang et al. 2019). As shown in Figure 8(f), when the concentrations of Ca\(^{2+}\) and SO\(_4^{2-}\) are low, the samples are distributed near the 1:1 equilibrium line, and the two ions mainly from the dissolution of gypsum. With an increase in ion concentrations, the water sample points deviate above the 1:1 equilibrium line, indicating the presence of Ca\(^{2+}\) from nonwater-rock interaction sources in karst water, and high concentrations of Ca\(^{2+}\) and SO\(_4^{2-}\) may be related to atmospheric precipitation and pollutant mixing (Yang et al. 2019). According to the abovementioned analysis of ion relationships,
the hydrochemical evolution of regional groundwater is controlled by the dissolution process of carbonate minerals and human factors. The mixing of other water bodies caused by human activities has become an important factor affecting changes in water quality.

4.4.2. Groundwater quality changes caused by human activities

Refer to previous research results, the conventional components in karst groundwater in spring areas have been increasing since 1959, especially since the 1980s. The increasing rate of each component has been accelerating, and the groundwater quality has been gradually deteriorating (Guan et al. 2019). In 2012, each component in groundwater increased, decreased, and then slowly increased (Sun et al. 2018). As the social economy has developed, the changes in groundwater quality caused by human activities show different characteristics in different regions. The karst water quality in the indirect recharge area in the southern part of the spring area fluctuates under the influence of the recharge source and the ecological environment. The karst water in the direct recharge area in the central part of the spring area is affected by the pollution of agriculture, animal husbandry and rural life, with high nitrate contents and slightly poor water quality. The discharge area is affected by industries and cities under the influence of domestic pollution; the water quality is poor; and the ion content in a few areas in the northeastern part of the spring area exceeds the standard.

In recent years, The urban area of Jinan increased from 204.49 km² in 2000 to 515.38 km² in 2015; the construction land area increased from 749.00 km² in 2000 to 1250.30 km² in 2015, and the cultivated land area decreased from 1015.43 km² in 2000 to 691.35 km² in 2015 (Meng 2017). With a large number of people living in the east, the urban sewage pipe network has been gradually improved, and the environmental governance capacity has been strengthened, which has directly influenced the land. The reduction in cultivated land area and increase in hard surface area reduce the direct input of chemical fertilizer, pesticide and other pollutants into groundwater. Therefore, the results of projection pursuit evaluation show that the water quality of groundwater in the eastern spring region is improving under the influence of human activities.

In the direct recharge area in the middle of the spring area, Jinan has implemented the project of converting surface water into groundwater since 2013. The western route project in the Yufu River mainly uses the raw water from Yuqing reservoir and Quehua reservoir to supply the groundwater through the Yufu River seepage area. The middle route of the project mainly uses the water from Jinxixuan Reservoir and Daming Lake to recharge groundwater through the strong seepage area of Liyang lake and Xingji River.

The direct recharge of surface water slows the decreasing spring water level and basically maintains the continuous gushing of spring water. But a large number of conventional ions in surface water are also input at the same time. For example, the content of SO\text{4}^2⁻ in groundwater after recharge is higher than the background value before recharge (Li 2019), which then affects the groundwater quality in the central and western spring area.

Therefore, human factors have become another key factor affecting the evolution of regional water quality after natural factors.

4.5. Analysis of pollution sources by the APCS-MLR model

4.5.1. Identification of pollution sources

The original data were transformed by range standardization. Kaiser Meyer Olkin (KMO) and Bartlett sphericity test were used to test the correlation degree between variables. The KMO measure was 0.601 > 0.5, which was suitable for factor analysis. The Bartlett sphericity test statistic was 781.147 (P = 0.00 < 0.05), indicating that there was a strong correlation between variables (Zhang et al. 2020b). Through PCA/FA analysis, the characteristic values and variance contribution rates of the water quality indexes were obtained. The results are shown in Table 4. The first four principal components were extracted with eigenvalues >1, explaining 72.378% of the total variance in the water quality dataset.

To make the typical representative index variables of common factors more prominent, orthogonal transformation of the factor load matrix is carried out. The main indicator ions with the strongest correlation between the rotating index load and the 1 or 0 polarization are shown in Table 5 and are expressed in bold font.

The first principal component F1 has a characteristic value of 3.145, and the variance contribution rate is 31.45%. The main load variables include Ca\text{2+}, HCO₃⁻, NO₃⁻, and the TDS water quality index. As the primary influencing factor of groundwater quality in the study area, F1 includes three of the eight main ions in groundwater, of which the NO₃ load coefficient is the highest, and the main sources of NO₃ are the application of
### Table 4 | The explanation of total variance

| Component | Initial Eigenvalues | Explanation rate of variance % | Explanation rate of cumulative variance % | Explanation rate of variance % | Explanation rate of cumulative variance % | Sum of squares of rotation |
|-----------|---------------------|---------------------------------|--------------------------------------------|---------------------------------|--------------------------------------------|-----------------------------|
|           |                     |                                 |                                            |                                 |                                            |                             |
| 1         | 3.145               | 31.446                          | 31.446                                     | 3.145                           | 31.446                                     | 2.143                       |
| 2         | 1.692               | 16.917                          | 48.363                                     | 1.692                           | 16.917                                     | 2.077                       |
| 3         | 1.348               | 13.476                          | 61.839                                     | 1.348                           | 13.476                                     | 1.833                       |
| 4         | 1.054               | 10.539                          | 72.378                                     | 1.054                           | 10.539                                     | 1.185                       |
| 5         | 0.703               | 7.028                           | 79.406                                     |                                 |                                            |                             |
| 6         | 0.648               | 6.48                            | 85.886                                     |                                 |                                            |                             |
| 7         | 0.509               | 5.093                           | 90.979                                     |                                 |                                            |                             |
| 8         | 0.406               | 4.062                           | 95.041                                     |                                 |                                            |                             |
| 9         | 0.346               | 3.458                           | 98.499                                     |                                 |                                            |                             |
| 10        | 0.15                | 1.501                           | 100                                        |                                 |                                            |                             |
general agricultural fertilizer and domestic wastewater (including landfall leachate) (Wu et al. 2017). Therefore, the first principal component can be identified as the urban life agriculture nonpoint source.

The contribution rate of the variance in the second principal component F2 is 16.917%, and the main load variables include the $\text{SO}_4^{2-}/\text{C}_0$, $\text{Cl}^-/\text{C}_0$, and $\text{NO}_3^-/\text{C}_0$ water quality indexes. The load coefficients of $\text{SO}_4^{2-}/\text{C}_0$ and $\text{Cl}^-/\text{C}_0$ are higher. Generally, $\text{Cl}^-/\text{C}_0$ is mainly produced from the dissolution of salt and from oxidants, and $\text{SO}_4^{2-}/\text{C}_0$ is mainly detected in industrial waste gas and enters groundwater in the form of atmospheric precipitation (Zhang et al. 2019). Therefore, the second principal component can be identified as industrial pollution.

The contribution rate of the third principal component is 13.476%. The main load variables are $\text{K}^+$, $\text{Na}^+$, $\text{Ca}^{2+}$ and other physical factor variables. These variables comprise the common source of minerals and are more likely caused by the dissolution of limestone and gypsum (Samsudin et al. 2017). The runoff conditions are relatively good, and the strong alternating action makes the dissolution of calcium and magnesium compounds in the rock stratum become $\text{Ca}^{2+}$ and $\text{Mg}^{2+}$ (Meng et al. 2017). The third principal component can be identified as geological mineral dissolution.

The characteristic value of the fourth principal component F4 is 1.054, and the variance contribution rate is 10.539%. The main load variables include $\text{SO}_4^{2-}/\text{C}_0$, $\text{Mg}^{2+}$, $\text{Ca}^{2+}$ and other water quality indexes. These factors are mainly affected by human activities (Meng et al. 2017). Therefore, the fourth principal component can be identified as the urban life source.

### 4.5.2. Contribution rate of pollution sources

The contribution rate of common factors to water quality indexes is calculated by APCS-MLR model. According to the calculation results (Table 6), the $R^2$ of the linear fitting between the predicted concentration and the measured concentration of the multiple linear regression model for each water quality index in the study area is between 0.79 and 0.93, which shows that they are consistent. In addition, the ratio of the predicted concentration to the measured concentration at each monitoring point is near 1, which indicates that the APCS-MLR model has good applicability for the calculation and allocation of pollution sources in the study area and that the calculation results are more reliable.

In conclusion, the contribution rates of the four common factors to the groundwater quality are 41.56, 22.91, 17.11 and 13.97%, respectively. The influence of urban life agricultural nonpoint sources, industrial enterprise pollution, geological mineral dissolution and urban life nonpoint sources on groundwater quality is more significant.

### 4.6. Indication of groundwater quality evolution

According to the water quality evaluation and hydrochemical characteristics analysis in recent years, the content of ionic components in karst water is increasing continuously along the groundwater flow in the spring area. Atmospheric precipitation infiltrates into the surface of the mountainous area in the southern to recharge karst water. After long-distance runoff circulation, the spring group flows out. Therefore, the geological
environments in the southern spring area are the key to determining the quality of spring water in the urban area. To prevent the water quality from deteriorating, it is necessary to strengthen the ecological and environmental protection of the southern spring area; to prevent damage to urban expansion in the southern recharge area, the policy of returning farmland to forest to protect the spring water quality should be implemented.

Presently, the project of converting surface water into groundwater is being implemented in western Jinan. While increasing the infiltration amount of surface water and raising the underground water level, more attention should be given to the quality monitoring of supplementary source water to prevent groundwater source pollution and achieve spring protection in terms of both ‘quality’ and ‘quantity’. In water scarce districts, there is no enough fresh water directly used for production and living. Brackish water and seawater desalination technology (Panagopoulos 2021b) can be used to obtain more fresh water resources to alleviate water pressure. At present, the production and domestic water demand in Jinan reaches 900,000 tons per day. With the development of economy, it is estimated that the daily water demand will reach 1.2 million tons in 2035, and the huge water demand will cause supply pressure on the limited freshwater resources in the city. At the same time, a large amount of salt water is distributed in the northwestern part of the study area, north of the Yellow River. So these salt water can be transformed into fresh water resources through seawater desalination technology to solve the problem of water resource shortage.

In the densely populated area in the middle of the spring area, we should improve the construction of urban drainage pipe networks and sewage treatment plants, collect and treat the domestic sewage of urban residents, recycle sewage and reduce the pollution of domestic sewage in groundwater. In agricultural areas, we should promote green agriculture, reduce the use of chemical fertilizer and insecticides, use more organic fertilizer, and properly use high-efficiency, low-toxicity and low-residue agricultural antibiotics.

In the intensive industrial area in the eastern part of the spring region, factories and enterprises should be rationally distributed, new technologies and processes should be adopted, backward production technology should be reformed, and industrial water recycling technology should be increased to reduce the pollution of groundwater caused by the ‘three wastes’.

5. CONCLUSION

The groundwater environment in karst areas is complex, vulnerable and changeable, and the water quality is easily disturbed by the external environment. Using a stable and reliable optimization model to scientifically and reasonably evaluate the water quality in the study area is of great significance for the protection of the regional karst water environment. In this study, the single factor method and the PPA optimization model based on the artificial intelligence algorithm (AMFO) were used to evaluate the karst water quality in the Jinan spring area. Because the PPA evaluation model comprehensively considers the weight of each factor in the water quality evaluation and the correlations between each of the factors, the evaluation results can better

Table 6  | Percentage of contributions (%)

| Parameters (mg/L) | Contribution | F1 | F2 | F3 | F4 | Unidentified sources | observed | predicted | Ratio | R² |
|-------------------|--------------|----|----|----|----|----------------------|----------|-----------|-------|----|
| K⁺                | 6.6          | 18.37 | 69.26 | 5.26 | 0.51 | 1.12 | 1.09 | 1.0275 | 0.85 |
| Na⁺               | 23.49        | 0.341 | 69.36 | 6.29 | 0.519 | 25.31 | 25.34 | 0.9988 | 0.791 |
| Ca²⁺              | 73.64        | 13.45 | 7.83 | 1.08 | 4 | 113.79 | 113.76 | 1.0005 | 0.83 |
| Mg²⁺              | 15.27        | 15.51 | 3.77 | 64.37 | 1.28 | 19.72 | 19.69 | 1.0015 | 0.89 |
| Cl⁻               | 10.36        | 79.23 | 1.59 | 0.61 | 8.21 | 54.88 | 54.89 | 0.9998 | 0.91 |
| SO₄²⁻             | 23.55        | 75.15 | 0.13 | 0.64 | 0.53 | 110.65 | 110.64 | 1.0001 | 0.95 |
| HCO₃⁻             | 64.55        | 2.66 | 16.78 | 7.47 | 8.74 | 237.18 | 237.16 | 1.0001 | 0.89 |
| F⁻                | 11.23        | 18.19 | 26.45 | 37.51 | 6.62 | 2.23 | 2.19 | 1.0183 | 0.92 |
| NO₃⁻              | 64.31        | 31.24 | 1.38 | 0.89 | 2.18 | 39.83 | 39.81 | 1.0005 | 0.90 |
| TDS               | 76.91        | 2.19 | 6.41 | 5.58 | 8.91 | 454.62 | 453.32 | 1.0029 | 0.88 |
| Average           | 41.56        | 22.91 | 17.11 | 13.97 | 4.45 |
reflect the real water quality situation in the study area. The evaluation results show that the groundwater quality in the spring area is mainly class II, class III and class IV. With the strengthening of environmental governance, the proportion of class II and class III water is expanding, class IV and class V water are significantly reduced, and the overall regional water quality is improving. The driving factors of water quality evolution in the study area include both artificial recharge and source supplementation and natural factors such as carbonate mineral dissolution. They jointly control the distribution of water quality and its evolution trend. The main pollution sources of groundwater include urban living nonpoint sources, industrial enterprise pollution, geological environment mineral dissolution and urban living non-point sources. Urban nonpoint sources have a significant impact on groundwater quality. The results can provide valuable information for regional water quality prediction, geological environment risk assessment and formulating reasonable water resource management strategies.

In the process of applying PP model, special attention should be paid to reasonably selecting the measured data and obtaining the samples data as much as possible to ensure the accuracy of the comprehensive evaluation results. At present, the selection of water quality evaluation indicators is mainly based on the national standards. However, trace organic contaminants, TOrCs that may cause cancer and teratogenesis have been continuously detected in groundwater in recent years, such as persistent organic pollutants (POPs), antibiotics, estrogen, etc. Countries around the world have not yet formulated and implemented clear control standards or regulations for TOrCs. The standard and objectives, species list and concentration limits of these matters are not clear, How to use artificial intelligence optimization model to quickly identify TOrCs and make a more real and accurate evaluation of water quality is still the focus of future research.

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CONFLICT OF INTEREST
The authors have no financial or proprietary interests in any material discussed in this article.

DATA AVAILABILITY STATEMENT
All relevant data are included in the paper or its Supplementary Information.

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