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Application of PCA-RSR Model in Reservoir Water Quality Evaluation

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ABSTRACT

Water quality evaluation is a critical component of water environmental quality management, and conducting water quality assessments for reservoirs is quite practical. The inaccuracy induced by information overlap of several water quality measures is rarely taken into account in current water quality assessment systems. To solve this problem, the Principal component analysis-Rank sum ratio (PCA-RSR) water quality evaluation model was used to quantitatively evaluate the water quality of the Daheiting reservoir based on the monitoring data of different water layers in 2019. The results show that the water quality of Daheiting reservoir in 2019 is slightly better than that of the end of the reservoir, due to the influence of human factors downstream of the Upper Panjiakou Dam and the topography of the Luan River System, and the water quality from the dam head to the reservoir tail shows a decreasing trend. The PCA-RSR model has a good correlation with the traditional water quality indexes (WQI) system, which can avoid errors caused by overlapping information among the indexes while also taking into account the weight of the environmental factors of the study area. It is feasible and has some practical value in reservoir water quality evaluation..

INTRODUCTION

The reservoir is an important source of drinking water in China, which plays an indispensable role in social life, such as water storage, flood control, power generation, and so on (Li et al. 2020). In recent years, as the social economy has developed, it has been common to notice an increase in pollution sources, the influence of environmental quality, and the loss in reservoir self-purification capacity due to human causes (Wang et al. 2020, Zhang et al. 2020a). It is necessary to conduct a comprehensive and reasonable scientific evaluation of the reservoir water environment to reduce the negative effects of human activities on the reservoir environment, identify the main pollutants in reservoir water quality, and establish a scientific and effective management system for the reservoir water environment (Xing Wei 2020).

Water quality evaluation is a method of qualitative and quantitative evaluation of the water quality of the target area according to the relevant environmental quality standards based on the field monitoring data (Song et al. 2017). At present, the main water quality evaluation methods are the fuzzy comprehensive evaluation method, artificial neural network method, water poverty index model method, and so on. For example, Yan & Yan (2015) have used the fuzzy comprehensive evaluation method to evaluate and forecast the water quality of the upper reaches of Dahuofang Reservoir and established the Nonlinear regression model of the Fuzzy Comprehensive Evaluation Index of water quantity and water quality, which has a high fitting effect, the water quality of each section can be predicted. Jiang et al. (2018) used the entropy evaluation method and fuzzy comprehensive evaluation method to evaluate the water quality in Baicheng, Jilin province, making the results of water quality evaluation more objective.

Sun et al. (2019) used the Modified Fruit Fly Optimization Algorithm-Extreme Learning Machine (MFOA-ELM) method to evaluate the water quality in Chao Lake, improving the predictability. The RBF neural network outperforms the standard neural network when it comes to data mining. It has a straightforward structure and a high degree of generality. Cao (2019) applied RBF Neural Network to quantitatively evaluate the water quality of the Reservoir in the south of Yanshan Mountain and proved that this method has the advantages of simple dimension expansion and is highly transplantable compared with the traditional method in the process of water quality evaluation. Based on the water poverty theory, Liu et al. (2016) constructed the water poverty evaluation index system, measured the water poverty degree of Gansu province, explored the spatial-temporal differentiation and driving factors, and innovated the index system of water quality evaluation. Although the preceding approaches have advantages in evaluating water quality, there are still some issues that need to be addressed, such as the complexity of fuzzy comprehensive evaluation and the subjectivity of selecting the index weight vector. The center vector and normalizing constant of the hidden layer radial basis function must be determined by the RBF Neural Network, which increases the challenge of building the model.

In the reaction region, the water poverty theory is more focused on the overall degree of water scarcity, and the effect of environmental pollutants on water quality is given less weight in the evaluation process. Furthermore, because the aquatic environment is such a complex organic whole, the mistake produced by information overlapping across multiple water quality parameters is rarely taken into account in standard water quality assessment methodologies. Principal component analysis (PCA) is based on the concept of dimension reduction, and it can effectively alleviate the error caused by information overlap by transforming most indexes into a few comprehensive indexes. Li et al. (2018a) combined the PCA with the water quality identification index method to evaluate the water quality of the Tokto section of the Yellow River and found that this method can accurately and objectively reflect the water quality characteristics. The rank-sum ratio (RSR), which uses the relative size relationship of data to show tiny changes, sort and classify each evaluation item, and split the pros and cons, can be used to show small changes, sort and classify each evaluation object, and divide the pros and cons. In data analysis, it is a frequent strategy for comparing and finding associations.

Xu et al. (2015) employed the RSR complete evaluation approach to objectively and accurately evaluate the water quality of swimming pools, indicating the need for sanitary supervision and improvement of swimming pool water quality. For water quality evaluation, combining PCA and RSR can effectively reduce errors caused by information overlap while correctly classifying and ranking the evaluation items. Using Daheiting Reservoir as an example, this work introduces the PCA-RSR water quality evaluation model and explores the feasibility and practical relevance of this model in reservoir water quality evaluation by comparing it to the widely used water quality indexes (WQI) approach.

MATERIALS AND METHODS

PCA is a mathematical dimensionality reduction method in the field of statistics. Its principle is to use orthogonal transformation to transform a series of possible related variables into a new group of linearly independent variables. The new variable is the extracted principal component, which can retain the information of the original variables as much as possible while reducing the number of original variables. It is widely used in the selection of water quality evaluation indicators and water environment quality assessment (Li et al. 2018b, Yu et al. 2017a, Liu et al. 2014, Liu et al. 2018, Ma et al. 2017, Yu et al. 2017b).

On the premise of ensuring the minimum loss of initial information, it can objectively divide the weights of different factors through statistical methods, and select the factors that have a great influence on the research objectives, to reflect the characteristics of the research objectives more effectively and intuitively. It avoids the subjective arbitrariness of the traditional water quality analysis methods (pollution index method, fuzzy comprehensive evaluation method, etc.), and has unique advantages. RSR is a statistical method that combines classical parametric statistics and modern nonparametric statistics. It has both advantages and was first put forward by Tian (2002). The principle is that in a matrix with n rows and m columns, the data is ranked by distinguishing high-quality and low-quality indexes according to the specified standards, and then through rank substitution, the dimensionless statistics RSR is obtained, and then combined with the method of parameter analysis to solve the problems of comprehensive evaluation encountered in various industries. It is a kind of statistical analysis method with strong pertinence and flexibility, which is widely used in the classification of various disciplines and the comprehensive evaluation of measurement data.

A water environment system is a complex system formed by the interrelation and comprehensive action of many kinds of water quality factors. And there are different degrees of correlation between different water quality factors, to avoid the problem of overlap and concealment of water quality information caused by direct evaluation of water quality monitoring data. PCA is utilized in this study to examine and determine the contribution rate of each water quality variable to the selected main components, as well as to keep the leading water quality factors. Furthermore, the PCA-RSR model is developed to quantitatively evaluate the water quality of the Daheiting reservoir using the parameters required by PCA results, and the evaluation results are visualized using Geographic Information System (GIS) technology. At the same time, the reservoir's WQI is calculated, and the model's feasibility and superiority in water quality evaluation are investigated by comparing it to the traditional method.

Calculation of WQI

WQI is one of many water quality assessment methods. It integrates and extracts the information of water quality monitoring data through mathematical tools, thus quantifying the degree of water pollution. The results are simple and intuitive.

It is widely used in water quality assessment at home and abroad. In this study, total nitrogen (TN), total phosphorus (TP), ammonia nitrogen (NH_3-N), nitrate-nitrogen (NO_3-N), Sulfate, Chloride, permanganate index (COD-Mn), chemical oxygen demand (COD), five-day biochemical oxygen demand (BOD_5), conductivity (EC), pH and other water quality indexes were selected to calculate WQI according to formula (1) (Pesce & Wunderlin 2000, Kocer & Sevgili 2014).

$$WQI = \sum_{i=1}^{n} C_i P_i \,/\, \sum_{i=1}^{n} P_i \qquad \ldots(1)$$

In the formula, n is the total number of water quality parameters, C_i is the normalized value assigned to parameter i, P_i is the relative weight of parameter i, and the range is 1-4 (Table 1). Referring to the present situation of water quality control in the Daheiting reservoir, the pollution of TP is serious, which is the main factor of water quality pollution (Wang 2020). Therefore, the TP weight was revised to 4.

PCA-RSR Water Quality Evaluation Model

PCA Analysis

1) Standardize the original data

The original data are standardized according to formulas (2) and (3).

$$\tilde{x}_{ij} = \frac{x_{ij}-\bar{x}_j}{s_j},\ (i=1,2,\ldots,n;\ j=1,2,\ldots,m) \qquad \ldots(2)$$

$$\bar{x}_j = \frac{1}{n}\sum_{i=1}^{n} x_{ij},\quad s_j = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(x_{ij}-\bar{x}_j\right)^2},\quad (j=1,2,\ldots,m) \qquad \ldots(3)$$

In the formula, m is the number of index variables and n is the number of evaluation objects $\tilde{x}_j$ and s_j are the sample mean and standard deviation of the j Index, x_{ij} is the value of the j Index of the i evaluation object $\tilde{x}_{ij}$ is the standardized indicator value.

2) Calculate the correlation coefficient matrix

Correlation coefficient matrix $R = (r_{ij})_{m*m}$

$$r_{ij} = \frac{\sum_{k=1}^{n}\tilde{x}_{ki}\cdot\tilde{x}_{kj}}{n-1},\ (i,\ j=1,2,\ldots,m) \qquad \ldots(4)$$

In the formula, $r_{ii}=1$, $r_{ij}=r_{ji}$, r_{ij} is the correlation coefficient between the i index and the j index.

3) Calculate eigenvalues and Eigenvectors

Calculate the eigenvalues of the correlation coefficient matrix R: $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_m \geq 0$, and the corresponding eigenvectors: $u_1, u_2, \ldots, u_m$. Among them, $u_j = (u_{1j}, u_{2j}, \ldots, u_{nj})^T$. m new indicator variables composed of eigenvectors:

$$\begin{cases} y_1 = u_{11}\tilde{x}_1 + u_{21}\tilde{x}_2 + \cdots + u_{n1}\tilde{x}_m \\ y_2 = u_{12}\tilde{x}_1 + u_{22}\tilde{x}_2 + \cdots + u_{n2}\tilde{x}_m \\ y_m = u_{1m}\tilde{x}_1 + u_{2m}\tilde{x}_2 + \cdots + u_{nm}\tilde{x}_m \end{cases} \qquad \ldots(5)$$

In the formula, y_1 is the first principal component, y_2 is the second principal component, …., y_m is the m-th principal component.

4) Calculate the contribution rate of principal component eigenvalues

The contribution rate (W'_i) of λ_i is calculated by the formula (6).

$$W'_i = \frac{\lambda_i}{\sum_{i=1}^{P}\lambda_i} \qquad \ldots(6)$$

Determination of Principal Component Weight Coefficient by RSR

The contribution rate of the eigenvalues of the extracted principal components is taken as the empirical weight coefficient (Zhang et al. 2020b), and the weight coefficient (*W*) is determined by SR in the RSR method according to the following steps.

The extracted principal components are horizontally sorted according to the low excellent index by the integral rank method to determine the rank R, and the RSR is calculated according to the formula (7).

$$RSR = \frac{\Sigma R}{k\cdot m} \qquad \ldots(7)$$

In the formula, ΣR is the rank-sum, that is, the rank synthesis of each index; k is the number of evaluation objects, that is, the number of monitoring samples; m is the number of evaluation indexes, that is, the number of principal components extracted.

The Sum Ratio (SR) was calculated according to formula (8).

$$SR = RSR/\Sigma RSR \qquad \ldots(8)$$

The *W* of each evaluation index was calculated according to formula (9).

$$W = (SR*W')/\Sigma(SR*W') \qquad \ldots(9)$$

In the formula, *W'* is the contribution rate of the eigenvalues of the extracted principal components.

Establishment of PCA-RSR Model

According to the principal components extracted by PCA and the weight coefficients determined by the RSR method, and combined with the standardized water quality evaluation grade, the threshold value of each water quality evaluation grade was calculated by Formula (10).

$$F_i = W_i * n_i * P_i \qquad \ldots(10)$$

In the formula, F_i is the critical threshold of all levels of water quality evaluation grade; P_i is the standardized data of water quality index corresponding to each grade; W_i is the weight coefficient of each evaluation index; n_i is the principal component load coefficient extracted by PCA.

Table 1: The relative weights and the normalization factors of parameters for WQI calculation.

indexes 100		Normalization factor (Ci)											Relative weight (P_i)
		90	80	70	60	50	40	30	20	10	0		
TN	/(mg.L^{-1})	<0.1	<0.2	<0.35	<0.5	<0.75	<1	<1.25	<1.5	<1.75	>2	>2	2
TP	/(mg.L^{-1})	<0.01	<0.02	<0.05	<0.1	<0.15	<0.2	<0.25	<0.3	<0.35	≤0.4	>0.4	4
NH_3-N	/(mg.L^{-1})	<0.01	<0.05	<0.1	<0.2	<0.3	<0.4	<0.5	<0.75	<1	≤1.25	>1.25	3
NO_3-N	/(mg.L^{-1})	<0.5	<2	<4	<6	<8	<10	<15	<20	<50	≤100	>100	2
NO_2-N	/(mg.L^{-1})	<0.005	<0.01	<0.03	<0.05	<0.1	<0.15	<0.2	<0.25	<0.5	≤1	>1	2
TON	/(mg.L^{-1})	<0.05	<0.1	<0.2	<0.3	<0.4	<0.5	<0.7	<1	<2	≤3	≥3	2
DO	/(mg.L^{-1})	<7.5	>7	>6.5	>6	>5	>4	>3.5	>3	>2	>1	<1	4
Phosphate	/(mg.L^{-1})	<0.16	<1.60	<3.20	<6.40	<9.60	<16.0	<32.0	<64.0	<96.0	>160.0	>160.0	1
Sulfate	/(mg.L^{-1})	<25	<50	<75	<100	<150	<250	<400	<600	<1000	>1500	>1500	2
Chloride	/(mg.L^{-1})	<25	<50	<100	<150	<200	<300	<500	<700	<1000	>1500	>1500	1
COD-Mn	/(mg.L^{-1})	<1	<2	<3	<4	<5	<8	<10	<12	<14	≤15	>15	3
COD	/(mg.L^{-1})	<5	<10	<20	<30	<40	<50	<60	<80	<100	≤150	>150	3
BOD_5	/(mg.L^{-1})	<0.5	<2	<3	<4	<5	<6	<8	<10	<12	≤15	>15	3
EC	/(μS.cm^{-3})	<750	<1000	<1250	<1500	<2000	<2500	<3000	<5000	<8000	≤12000	>12000	1
pH		7	7-8	8-8.5	8.5-9	6.5-7	6-6.5 or 9-9.5	5-6 or 9.5-10	4-5 or 10-11	3-4 or 11-12	2-3 or 12-13	1-2 or 13-14	1

According to the principal components extracted by PCA and the weight coefficients of principal components determined by the RSR method, the water quality evaluation model of PCA-RSR was established, and the comprehensive evaluation value f of water quality at each monitoring site was calculated according to formula (11).

$$f = \sum_{i=1}^{n} W_i * F_n(x) \qquad \ldots(11)$$

In the formula, f is the comprehensive evaluation value of each monitoring point in the PCA-RSR water quality evaluation model; W_i is the weight coefficient of each evaluation index; $F_n(x)$ is the corresponding score of each principal component extracted by each monitoring point.

APPLICATION EXAMPLE

Study Area

Daheiting Reservoir is a drinking water source reservoir in the Luan River system, which belongs to the second type of water conservancy project (Li 2019). This reservoir (40°12′4″~40°21′18″N, 118°15′22″~118°19′21″E) is located in Qianxi County, Tangshan City, Hebei Province. The total reservoir capacity is about 340 million m^3, and the backwater length of the reservoir is about 23 km (Liu et al. 2019). It serves as the source reservoir for the Luan River diversion project, providing drinking water to Tianjin, Tangshan, and the cities along the Luan River's lower reaches.

Sample Collection and Determination

Five sampling points are uniformly arranged in the Daheiting reservoir area (Fig.1). The SX800 series portable electrochemical instruments (Shanghai San-Xin Instrumentation) is used to determine water quality indicators such as EC, pH, and other parameters at each sampling location. In addition,

Table 2: WQI water quality classification.

Range	Comprehensive water quality grade
WQI>80	I
80≥WQI>60	II
60≥WQI>40	III
40≥WQI≥20	IV
WQI<20	V

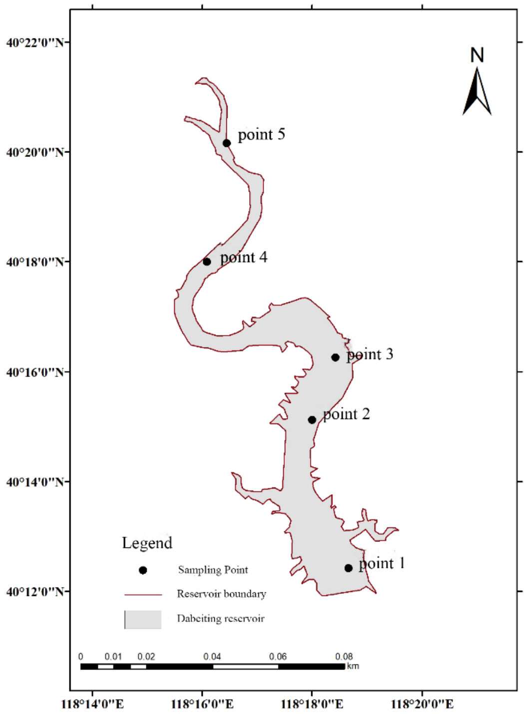

Fig. 1: Sampling point.

Table 3: Standardization of water quality evaluation grades and indexes.

	I	II	III	IV	V
TN	-1.11094	-0.45261	0.37031	1.19324	1.19324
TP	-1.1619	-0.3873	0.3873	1.1619	1.1619
NH_3-N	-0.97095	-0.45311	0.06473	1.35933	1.35933
NO_3-N	-0.72626	-0.53576	-0.2024	1.46442	1.46442
Sulfate	-0.78961	-0.61083	-0.0149	1.41534	1.41534
Chloride	-0.86603	-0.61859	0.12372	1.3609	1.3609
COD-Mn	-1.00673	-0.60404	0.40269	1.20808	1.20808
COD	-1.0247	-0.43916	0.14639	1.31747	1.31747
BOD_5	-1.02151	-0.51075	0.25538	1.27688	1.27688
EC	-0.7597	-0.51331	-0.18479	1.45781	1.45781
pH	-1.1619	-0.3873	0.3873	1.1619	1.1619

each sampling point was separated into three layers based on its actual water depth: the surface water body, the middle water body, and the bottom water body. Water samples of 500 mL were gathered from each layer. The water samples were transported back to the laboratory according to the corresponding water quality testing standards to determine TN, TP, NH_3-N, NO_3-N, sulfate, Chloride, COD-Mn, COD, BOD_5, and so on.

Evaluation Results of PCA-RSR Model

The monitoring data of each index in this monitoring site and the corresponding water quality evaluation standards are standardized, and the standardized water quality evaluation standards are detailed in Table 3.

On this basis, the dimension reduction and principal factor extraction of the water quality indexes monitoring data of the collected water samples are further carried out. According to the extracted eigenvalues, the first five are selected as the principal components, and the load coefficient matrix n (Table 4) of each principal component and the contribution rate of the eigenvalues of each principal component is determined (W'=22.461, 21.092, 17.567, 10.647, 9.117).

The related indexes of the RSR method are calculated according to the formula (7) ~ (9). The results are given in Table 5.

According to the principal components extracted by PCA and the weight coefficients of principal components determined by the RSR method, combined with the standardized water quality evaluation grade, the threshold of each water quality evaluation grade is calculated according to formula (10). The calculation results are presented in Table 6.

According to the principal components extracted by PCA and the weight coefficients of principal components determined by the RSR method, the PCA-RSR water quality evaluation model is established. The comprehensive evaluation value f (formula (12)) of each monitoring point is calculated according to formula (11). The evaluation results are visually processed by ArcGIS software, as shown in Fig. 2.

$$f = 0.276049*F_1(x)+0.255296*F_2(x)+0.232257*F_3(x)+0.132836*F_4(X)+0.103561*F_5(x) \quad \ldots(12)$$

The evaluation result of the PCA-RSR model is a low-excellent index, that is, the smaller the value, the better the water quality. According to Fig. 2, from the longitudinal distribution, the water quality of different water layers near the tail of Daheiting Reservoir is poor, indicating that it is greatly affected by upstream water pollution; in the middle of the reservoir where Point 3 is located, due to the influence of topography, the curved river slows down the velocity of the water body, and the pollutants in the surface water can be deposited to the lower layer, resulting in slightly better water quality in the surface layer than in the bottom layer. The water area at the dam head is relatively large, and the larger water volume in the vast water region produces a pollutant-dilution impact. The water quality of distinct water strata at this location is in good shape as a result of this diluting effect. The water quality of the dam head is better than that of the reservoir's tail, and the water quality exhibits a diminishing tendency from the dam head to the reservoir's tail as a whole. Based on water quality monitoring data from Daheiting Reservoir in several seasons in 2018, Wu et al. (2020) assessed the water quality status of Daheiting Reservoir and found comparable results. Chen et al. (2016) found that nitrogen and phosphorus are not only the main pollutant of Daheiting Reservoir but also the main limiting factor of water eutrophication. In the PCA method, the higher the contribution rate of the extracted principal component is, the more information it contains, the greater the influence on the water quality. The water area at the dam head is relatively large, and the larger water volume in the vast water region produces a pollutant-dilution impact. The water quality of distinct water strata at this location is in good shape as a result of this diluting effect. The water quality of the dam head is better than that of the reservoir's tail, and the water quality exhibits a diminishing tendency

Table 4: Load Coefficient Matrix of each principal component.

	F1	F2	F3	F4	F5
TN	0.389	-0.151	-0.034	0.331	-0.117
TP	-0.048	0.25	0.268	0.214	-0.198
NH_3-N	0.108	0.201	0.221	-0.113	-0.176
NO_3-N	0.122	0.347	-0.308	0.258	0.071
Sulfate	0.321	-0.059	0.098	-0.158	-0.061
Chloride	0.065	-0.035	0.037	0.698	0.014
COD-Mn	0.094	0.006	-0.097	0.03	0.763
COD	0.075	-0.091	0.465	0.08	-0.094
BOD_5	-0.086	0.027	0.31	-0.036	0.269
EC	0.424	0.146	-0.099	-0.033	0.317
pH	0.091	-0.458	0.065	0.176	-0.093

Table 5: Results of RSR method.

	ΣR	RSR	SR	W
F1	66	0.6	0.2	0.276049
F2	65	0.590909	0.19697	0.255296
F3	71	0.645455	0.215152	0.232257
F4	67	0.609091	0.20303	0.132836
F5	61	0.554545	0.184848	0.103561

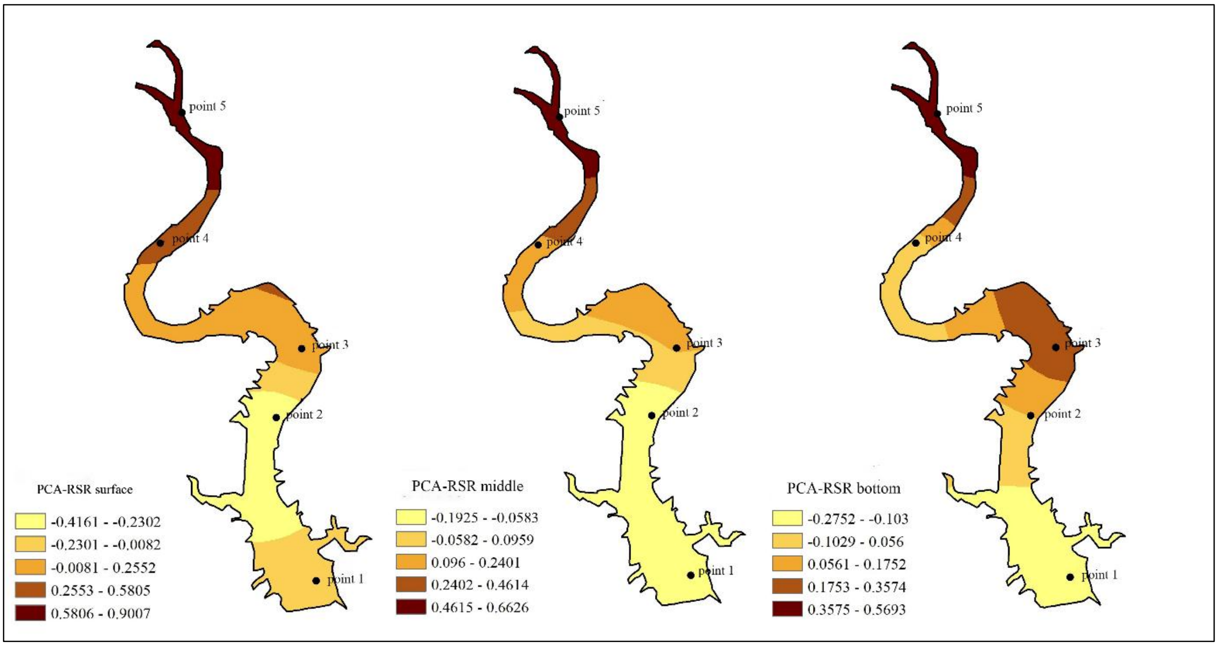

Fig. 2: PCA-RSR model evaluation results.

from the dam head to the reservoir's tail as a whole. Based on water quality monitoring data from Daheiting Reservoir in several seasons in 2018, Wu et al. (2020) assessed the water quality status of Daheiting Reservoir and found comparable results. The water quality is inevitably affected by the discharge of Panjiakou Reservoir upstream and by the inflow of Sa River upstream. The Sa river runs through the town of Sa river. Domestic sewage and iron ore industrial effluent are released into the Sa River and flow downstream to the Daheiting Reservoir (Li 2010). This could explain the high levels of nitrogen and phosphorus in the reservoir's upper reaches, as well as the poor water quality of the reservoir's various water layers. Furthermore, because the Luan River system's terrain tilts from northwest to southeast (Li 2019), Daheiting Reservoir has a unique geographical location, and the amount of water in each section varies. The wider water area and larger water volume in the lower reaches have a certain dilution effect on the water bodies with high nitrogen and phosphorus concentrations from the middle and upper reaches so that the water quality of the downstream dam head of the Daheiting Reservoir is better than that of the upstream reservoir tail. The water quality shows a decreasing trend from the head of the dam to the end of the reservoir as a whole.

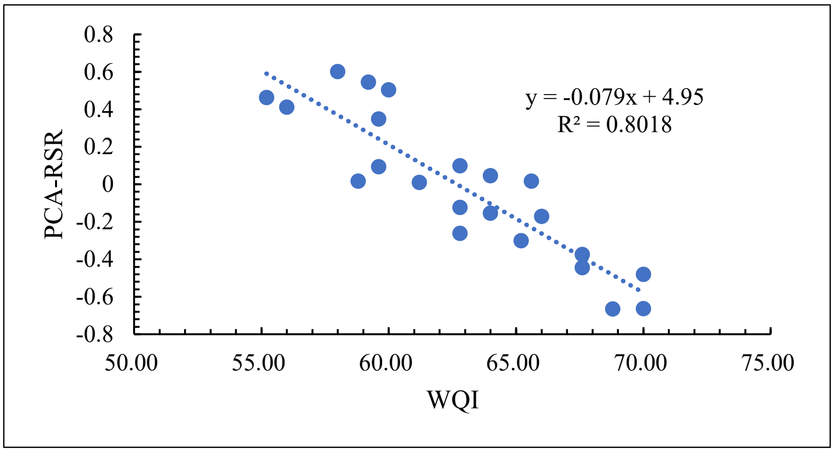

Fig. 3: Correlation between WQI and PCA-RSR model.

Comparison of Evaluation Results

According to Formula (1) and Table 1, the scores of each point in the WQI water quality evaluation model were calculated, and the scores were classified according to Table 2. At the same time, the scores of the PCA-RSR water quality evaluation model were classified according to Table 6. The results are shown in Table 7.

It can be seen from Table 7 that the WQI model is a high-excellent model and the PCA-RSR model is low-excellent. The evaluation results of the latter are in good agreement with those of the WQI system, which is widely used in water quality evaluation, indicating that the model is feasible in water quality evaluation. Under the same water quality conditions, this model's score and assessment grade are lower than the old WQI system, showing that this model's evaluation criterion is stricter than the WQI system'. The discrete coefficient can reduce the impact of the absolute value and measurement unit on the degree of discreteness measurement. The degree of discretization of the data is proportional to the discrete coefficient. The discretization coefficients of the evaluation score values of the two models are calculated according to the formula (13) and Table 7, respectively. The results show that the discretization coefficient (v_s=3.566) of the evaluation score values of the PCA-RSR model is larger than that of the WQI model (v_s=0.059), that is, the discretization degree of the evaluation score values of the PCA-RSR model is greater than that of the WQI system, indicating that the model is more precise in reflecting the differences between different water quality conditions. It can better show the differences between different water quality conditions.

$$v_s = \frac{s}{\bar{x}} \qquad \ldots(13)$$

In the formula, v_s is the discrete coefficient, s is the standard deviation of the group of data, is the average value of the group of data.

Excel 2019 is used to analyze the correlation between the evaluation results of WQI and the PCA-RSR model, which is detailed in Fig.3. The results show that there is a good negative correlation between them ($R^2 = 0.8018$), indicating that the evaluation system of the PCA-RSR model is feasible and has a certain application value.

CONCLUSION

(1) The spatial water quality variation of Daheiting Reservoir in 2019 shows that the water quality at the dam head is slightly better than that at the end of the reservoir. This is due to the influence of human factors along the Sa River, discharge

Table 6: PCA-RSR model threshold for water quality evaluation.

Grade	Range
I	$f \leq -0.88374$
II	$-0.88374 \leq f \leq -0.49191$
III	$-0.49191 \leq f \leq 0.098711$
IV	$0.098711 \leq f \leq 1.276935$
V	$f \geq 1.276935$

Table 7: Water quality assessment scores and ratings.

Sampling Point	depth	WQI score and rating		PCA-RSR score and rating	
1	surface	67.00	II	-0.1172	III
	middle	64.00	II	-0.21129	III
	bottom	67.60	II	-0.50956	II
2	surface	68.00	II	-0.41669	III
	middle	63.80	II	-0.42396	III
	bottom	62.00	II	0.054408	III
3	surface	59.60	III	0.154548	IV
	middle	62.60	II	0.282544	IV
	bottom	60.00	III	0.503783	IV
4	surface	56.00	III	0.312489	IV
	middle	59.60	III	0.073178	III
	bottom	62.80	II	-0.36057	III
5	surface	58.00	III	0.901332	IV
	middle	58.60	III	0.922751	IV
	bottom	59.20	III	0.944169	IV

from upstream Panjiakou Reservoir, as well as the topography of the Luan River system. From the dam head to the reservoir's end, the water quality is deteriorating.

(2) The PCA-RSR model is low-excellent. The water quality evaluation result has a greater correlation than the traditional WQI system. The evaluation criteria are more stringent than those used by the WQI method. The degree of discrimination shown between different water quality circumstances is larger and more precise than that of the old system.

(3) PCA-RSR model uses PCA to effectively avoid the errors caused by information overlap among various indicators, and fully considers the weight of environmental factors in the study area, which makes the evaluation system more suitable for this study area, has a certain practical value, and is suitable for water quality evaluation in specific research areas.

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