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A hybrid approach based on Monte Carlo simulation-VIKOR method for water quality assessment

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ABSTRACT

Under the dual influence of global climate change and human activities, river water environment is facing more and more serious problems and challenges. Assessing river water quality is of great significance for promoting regional sustainable development. Currently, traditional water quality assessment methods usually do not consider the uncertainty of water quality data in the collection process, which limits the application of these methods. In order to overcome the above shortcomings, this study constructed a water quality assessment method by integrating Monte Carlo method (MC), CRITIC and VIKOR methods, and applied it to assess the quality of water in the Songhua River tributary. Results indicate that: (1) The water quality assessment of the two sampling points in the study area is level III, which is consistent with the actual situation; (2) This method can overcome the uncertainty caused by sampling error and improve the credibility of water quality evaluation results; (3) Total nitrogen (TN), potassium permanganate index (PPI) and ammonia nitrogen (NH_3-N) are more evaluation factors related to the evaluation results. When the decision coefficient mechanism λ is taken [0.1–0.5], the outcomes are in line with the real quality of the water. In addition, we recommend that the distribution profile generated based on the measured data should obey the probability distribution density curve that decreases from the middle to the tail of both sides. The findings of this paper can provide a scientific basis for decision makers to carry out water quality restoration and management.

1. Introduction

Water ecosystem is an important part of the global environment. In addition to being important contributors to biodiversity and ecological productivity, they provide a variety of services to humans, including drinking and irrigation water, recreational opportunities and habitats for important economic fisheries. Water ecosystems are experiencing rapid degradation and depletion due to multiple factors such as population growth, land use change, agriculture and urban expansion. In addition, a large number of pollutants are discharged into rivers, resulting in water quality degradation and destruction of aquatic ecosystems, which in turn leads to changes in key ecosystem services provided by water bodies and the loss of biodiversity related to these services (Aznar-Sánchez et al., 2019; Bain et al., 2020; Faghihinia et al., 2021; Keeler et al., 2012; Li et al., 2018; Pandey et al., 2018). As the world's largest developing country, China's social development has put forward higher requirements for water quality, for which a series of measures have been implemented for water management, such as the implementation of the river chief system in the country (Wang et al., 2021). Since then, society has paid more attention to surface water such as rivers, which is the primary water source for human social and ecological protection, and its water quality condition directly affects the water security of the receiving area and even the sustainable development of the whole region (Chen et al., 2015; Li et al., 2018; Guo et al., 2020; Yang and Chen, 2021). Surface water quality is influenced by many factors and should be evaluated using a comprehensive evaluation method (Yan et al., 2022). However, water quality managers often face a changing and uncertain environment when conducting water quality assessments, which may result in uncertainties being ignored or simplified. Therefore, it is a challenging task to incorporate uncertain factors and establish a feasible and effective water quality assessment model, but it is very important for the water resources rationalization and comprehensive prevention and restoration of aquatic ecosystem.

Several comprehensive evaluation approaches have been used in river water quality assessment around the world. These methods mainly include (1) comprehensive indices (e.g., water quality indices and

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trophic status indices) (Ruan et al., 2021; Yan et al., 2022), These indices are relatively simple to calculate and can quickly identify water quality, but they cannot accurately reflect water quality when the water quality is in the middle of two ranges (Gao et al., 2022); (2) multivariate statistical analysis methods (e.g., principal component analysis (PCA) and cluster analysis (CA))(Horvat et al., 2021; Lee et al., 2020). PCA can extract the main independent comprehensive factors from multiple water quality indicators, and retain the original main information. However, PCA has the problem that the meaning is not clear when the coefficients of principal components are similar (Kallio et al., 2018). CA is a division based on the degree of data similarity and compares things from various categories to identify differences (Lee et al., 2020). However, the choice of similarity measures may result in different water quality assessments in the same area (Du et al., 2017); (3) artificial intelligence (e.g., artificial neural network (ANN) and support vector machine (SVM)) (Wang et al., 2019; Tiyasha et al., 2020). ANN can deal with the nonlinear relationship between the index and the level. However, it is easy to fall into local minima and overfitting defects in the learning process (Tiyasha et al., 2020). SVM is a risk minimization criterion that can obtain the global optimal solution, but its effect will be affected when dealing with numerous samples (Haghiabi et al., 2018). However, because of the dynamic and complex characteristics of the water environment itself, coupled with the advantages and disadvantages of these methods, different results may be shown when evaluating water quality in the same or different areas (Logez et al., 2019).

River water quality is impacted by several factors, and water quality managers usually choose appropriate methods and indicators of evaluation to identify water quality levels and carry out different water quality remediation measures according to their levels. Therefore, water quality evaluation can be regarded as a multi-criteria decision-making (MCDM) problem in essence (Yao et al., 2021). Currently, the method based on MCDM has been applied for assessing the water quality. Zahedi et al., (2017) adopted a MCDM model based on the ideal solution similarity prioritization method (TOPSIS) and the compromise programming method (CP) and applied it to water quality evaluation. The outcomes indicate that proposed method can provide accurate evaluation results.

Chen et al., (2019) developed a multi-objective decision-making integrated model (including TOPSIS, Grey Relational Analysis, analytical hierarchy process and Takagi-Sugeno fuzzy neural network) for water quality assessment, considering that different methods produce various outcomes to the uniform area, and verified the effectiveness of the integrated model in an example. Li et al. (2021) proposed an MCDM model that combines a decision-making trial and evaluation laboratory (DEMATEL) with TOPSIS to verify the model's accuracy in evaluating water quality. Ruan et al., (2021) proposed a MCDM technology based on a cloud model to evaluate water quality. The results indicate that the model is feasible and effective and can accurately reflect the quality of water. Among them, the TOPSIS model is commonly utilized in assessing water quality because of its simple use, small information distortion and no influence of reference sequence. However, in some cases, it may get unreasonable optimization order, which leads to the inability to correctly distinguish the advantages and disadvantages of different schemes (Zeng et al., 2020). Therefore, Opricovic and Tzeng proposed the VIKOR model in 1998, which can effectively represent the relative importance between indicators, achieve the balance between group benefits and individual regrets, and effectively make up for the defects of the TOPSIS model (Opricovic and Tzeng, 2004). Nowadays, the VIKOR method was commonly utilized in numerous areas. For example, Wang et al., (2018) used the VIKOR method to evaluate construction project risk and prioritize risk factors. Golfam et al., (2019) evaluated the optimal water supply management under climate change using the VIKOR method. Li et al. (2022b) used the VIKOR method to identify the risk status of submarine pipelines, and the results are beneficial to the management of submarine pipelines. However, there are few studies on VIKOR in water quality assessment.

In previous studies, few MCDM models took into account the uncertainty factors of water quality evaluation, especially the uncertainty caused by human factors in the data collection process. On the contrary, most of the MCDM models get the evaluation results under certain input data, and the water quality evaluation based on the MCDM method under uncertain input still needs further study. Therefore, it is urgent to establish a reliable river water quality assessment method to provide decision support for water quality managers.

Based on this, this study uses the MC method to randomly simulate water quality monitoring data, MC is an uncertainty method that widely deals with decision-making problems, which can effectively overcome the influence of human factors on data quality. Then, the CRITIC method is used to calculate the index weight. As an objective weighting method, it can ensure that the information of evaluation index data can be fully utilized and avoid subjective problems effectively. Finally, water quality was evaluated by VIKOR method. Specifically, we performed two main tasks:

(1) An evaluation method combining MC, CRITIC and VIKOR was developed to accurately diagnose water quality.
(2) The proposed method is used for studying the river water quality and identify the main influencing factors related to the evaluation results.

To better attain the aforementioned goals, this paper takes the Songhua River tributary as an example to evaluate the performance of the proposed method. This study can provide a reference for water quality managers to effectively evaluate water quality and water quality restoration.

2. Methodology

In this study, Monte Carlo, CRITIC and VIKOR methods are integrated to evaluate water quality. The proposed method includes: 1) overcoming the error during data collection based on the Monte Carlo method, 2) determining the weight of water quality indicators with consideration of description of the importance of multiple indicators effectively based on the objective weighting method (CRITIC), 3) obtaining the water quality level of sampling points by the combination of VIKOR method and membership function; and finally, the use of correlation analysis and sensitivity analysis to illustrate the feasibility of the proposed method. Fig. 1 shows the framework of the proposed method.

2.1. Monte Carlo simulation

The MC method is based on probability and statistics theory, which can be applied for analyzing a variety of uncertain issues (Seifi et al., 2020). It assumes that random variable's probability distribution function is known and improves the reliability of the output results by multiple sampling (Cimorelli et al., 2020). In the evaluation process, due to human factors and sampling errors in the data processing process, it is necessary to reduce the impact on the evaluation results. Therefore, this study uses MC method to overcome the uncertainty of sampling, and assumes that the water quality data obey Normal distribution (Table 4) (Ma et al., 2014), then the probability distribution curve can be written as:

$$f\left(x_{ij}^{MC}\right) = \frac{1}{\theta_j\sqrt{2\pi}}e^{-\frac{\left(x_{ij}^{MC}-\mu_j\right)^2}{2\theta_j^2}} \quad (1)$$

where, $f(\blacksquare)$ denotes the normal distribution function, $x_{ij}{}^{MC}$ represents the simulation value (from MC) of the jth index under the ith evaluation object, μ_j and θ_j are the mean and standard deviation of the distribution, respectively. In this study, θ_j is set to less than 5 % of the measured data.

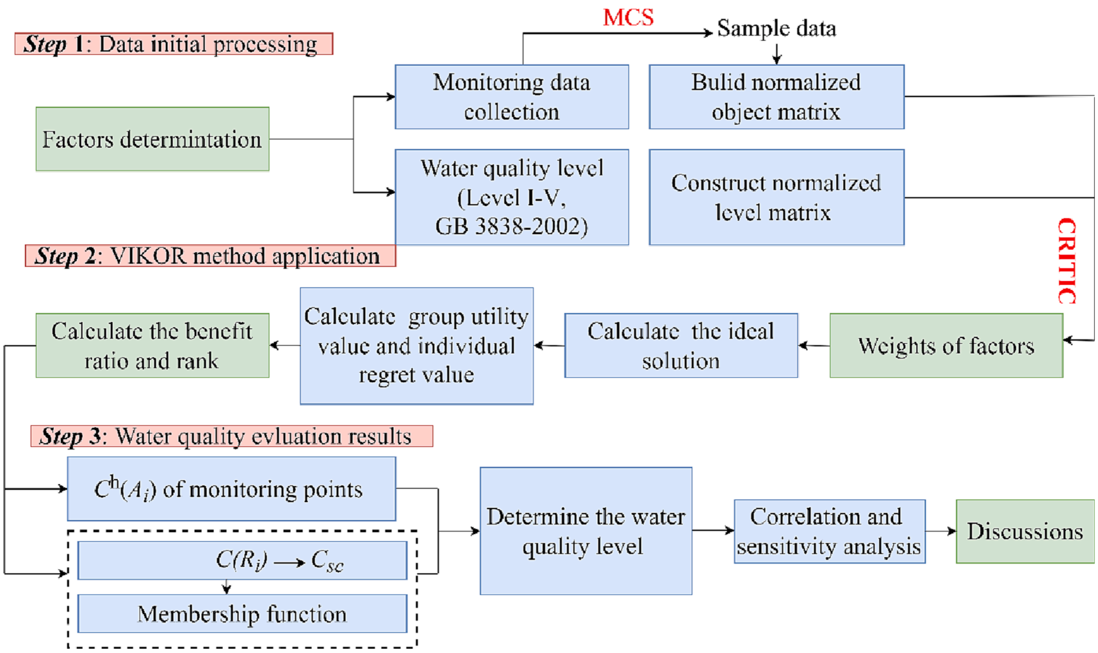

Fig. 1. Research route of this study.

2.2. *Weight determination method*

The determination of the evaluation factor weights is an important part of the water quality evaluation process, and the rationality of the weights directly affects the water quality evaluation results. Therefore, the weights in this paper are obtained using the CRITIC approach. It is used as an objective weighting approach to measure the indicator weights comprehensively according to the contrast intensity and conflict among indexes. The size of the difference in the values taken for the same index in different contexts is referred to as contrast intensity, which we express as the standard deviation. Conflict is the existence of a certain correlation between the indicators, and if two indicators have a high positive association, and there is little controversy (Li et al., 2018; Zhou et al., 2022; Yang, 2022). The calculation steps can be written as:

Step 1: Construct assessment matrix

$$B = \begin{bmatrix} b_{11}^{MC} & \cdots & b_{1n}^{MC} \\ \vdots & \ddots & \vdots \\ b_{m1}^{MC} & \cdots & b_{mn}^{MC} \end{bmatrix} \tag{2}$$

where, m and n represent the number of influencing factors and evaluation indexes respectively, and $b_{ij}{}^{MC}$ represents the jth evaluation index value under the ith influence factor.

Step 2: Data normalization.

To eliminate the influence of data dimensionality, the assessment index values need to be dimensionless.

$$\begin{cases} e_{ij} = \left(b_{ij}^{MC} - b_j^{MC\min}\right) \Big/ \left(b_j^{MC\max} - b_j^{MC\min}\right), costcriteria \\ e_{ij} = \left(b_{ij}^{MC\max} - b_j^{MC}\right) \Big/ \left(b_j^{MC\max} - b_j^{MC\min}\right), benefitcriteria \end{cases} \tag{3}$$

where, e_{ij} denotes the dimensionless data, and b_j^{max} and b_j^{min} denote the highest and lowest values of the evaluation indexes (including criteria value), respectively.

Step 3: Calculate the standard deviation (σ_j) of the representative value of variability within the evaluation index

$$\begin{cases} \bar{b}_j = \frac{1}{n}\sum_{i=1}^{n} e_{ij} \\ \sigma_j = \sqrt{\frac{\sum_{i=1}^{n}\left(e_{ij} - \bar{b}_j\right)^2}{n-1}} \end{cases} \tag{4}$$

Step 4: Calculate the correlation coefficient r_{ij} between indicators i and j by Eq. (5), and calculate the conflicting representative value C_j of the evaluation indicators according to the following formula (6).

$$r_{ij} = \frac{\sum\left(b_{ij}^{MC} - \overline{b_{ij}^{MC}}\right)\left(e_{ij} - \overline{e_{ij}}\right)}{\sqrt{\sum\left(b_{ij}^{MC} - \overline{b_{ij}^{MC}}\right)^2 \sum\left(e_{ij} - \overline{e_{ij}}\right)^2}} \tag{5}$$

$$C_j = \sum_{i=1}^{n}\left(1 - r_{ij}\right) \tag{6}$$

Step 5: Determine the j_{th} indicator's weight w_j

$$w_j = \frac{\sigma_j C_j}{\sum_{i=1}^{n}\sigma_j C_j} \tag{7}$$

2.3. *VIKOR method*

Opricovic and Tzeng proposed the VIKOR method in 1994 (Opricovic and Tzeng, 2004). Based on the determination of the positive and negative ideal schemes, VIKOR compares the distance among each objective and the optimal plan by calculating the maximum group benefit (S_i) value, the minimum individual regret value (R_i), and the benefit ratio value (Q_i), and finally ranks them (Khan et al., 2021). The formulas can be written as:

Step 1: Determine the positive ideal solution $b^{+}{}_j$ and the negative ideal solution $b^{-}{}_j$.

$$\begin{cases} b_j^{+} = \max\left(b_{ij}^{MC}\right) \\ b_j^{-} = \min\left(b_{ij}^{MC}\right) \end{cases} \tag{8}$$

Step 2: Calculate S_i and R_i for each alternative.

$$S_i = \sum_{j=1}^{n} w_j \left(b_j^+ - b_{ij}^{MC}\right) \Big/ \left(b_j^+ - b_j^-\right) \tag{9}$$

$$R_i = \max_j \left\{ w_j \left(b_j^+ - b_{ij}^{MC}\right) \Big/ \left(b_j^+ - b_j^-\right) \right\} \tag{10}$$

Step 3: Calculate the Q_i for each alternative.

$$Q_i = \lambda \frac{(S_i - \min S_i)}{(\max S_i - \min S_i)} + (1 - \lambda) \frac{(R_i - \min R_i)}{(\max R_i - \min R_i)} \tag{11}$$

where, $\lambda \in [0, 1]$ is the decision coefficient, set to 0.5 in this study.

2.4. Evaluation of water quality

To assess water quality, this paper uses the membership function to describe the relationship between the evaluated sampling points and different grades (Li et al., 2018), which can be written as:

$$\varphi_1[Q_i] = \begin{cases} 1, Q_i \in [0, Cs_1) \\ 1 - (Q_i - Cs_1)/(Cs_2 - Cs_1),\ Q_i \in [Cs_1, Cs_2) \\ 0, Q_i \in [Cs_2, 1) \end{cases} \tag{12}$$

$$\varphi_c[Q_i] = \begin{cases} 1 - (Q_i - Cs_{c-1})/(Cs_c - Cs_{c-1}), Cs_{c-1} < Q_i < Cs_c \\ 1 - (Cs_c - Q_i))/(Cs_{c+1} - Cs_c),\ Cs_c < Q_i < Cs_{c+1} \\ 0, 0 < Q_i < Cs_{c-1} \mathrm{or} Cs_{c+1} < Q_i < 1 \end{cases} \tag{13}$$

$$\varphi_5[Q_i] = \begin{cases} 1 - (Q_i - Cs_5)/(Cs_5),\ Q_i > Cs_5 \\ 1 - (Q_i - Cs_4)/(Cs_5 - Cs_4),\ Cs_4 < Q_i < Cs_5 \\ 0, Cs_5 < Q_i < 1 \end{cases} \tag{14}$$

where,$\varphi_5[Q_i] \in [0,1]$, Cs_i is the benefit ratio value of water quality grade, and the object's water qualitye can be written as:

$$G^h(Q_i) = \sum_{c=1}^{5} c \cdot \varphi_c[Q_i] \tag{15}$$

Where, $c = 2,3,4$; The water quality status depends on the distribution of $G^h(Q_i)$. Thus, this study divides water quality into five levels. (Table 1).

2.5. Correlation analysis

To assess the relationship between the input factors and the evaluation results, this study used Pearson correlation coefficient (PCC) for correlation analysis, which indicates the importance of each input object to the output results. PCC is expressed as follows:

$$R(Xj) = \frac{\sum_{h=1}^{H} \left[G^h(Q_i) - \overline{G^h(Q_i)}\right] \left[x_{ij}^h - \overline{x_{ij}^h}\right]}{\sqrt{\sum_{h=1}^{H} \left[G^h(Q_i) - \overline{G^h(Q_i)}\right]^2 \sum_{h=1}^{H} \left[x_{ij}^h - \overline{x_{ij}^h}\right]^2}} \tag{16}$$

where, $R(X_j)$ represents the correlation value of the j_{th} influencing factor to the output value $G^h(Q_i)$; H is the number of MC methods, in this study $H = 1000$; $G^h(Q_i)$ and $\overline{G^h(Q_i)}$ denote the water quality assessment results and the their average value at the h_{th} $^{\mathrm{MC}}$ iteration; x_{ij}^h and $\overline{x_{ij}^h}$ are the sample values and the average of the samples under the MC iteration.

Table 1
Water quality evaluation level classification.

Level	Classification of $G^h(Q_i)$
I	$0 \leqslant G^h(A_i) < 1.5$
II	$1.5 \leqslant G^h(A_i) < 2.5$
III	$2.5 \leqslant G^h(A_i) < 3.5$
IV	$3.5 \leqslant G^h(A_i) < 4.5$
V	$4.5 \leqslant G^h(A_i) < 5$

According to the output results of the developed model, the PCC between each input factor and the evaluation results is calculated. The range of is $R(X_j)$ [-1,1], where the greater the absolute value of $R(X_j)$, the stronger the correlation between input factors and evaluation results, and vice versa. It is useful to use correlation analysis because it enables watershed managers to carry out the next step more specifically, that is, to check the importance of these factors to water quality results in order to carry out water quality restoration work.

3. Study case and data sources

Based on the water quality evaluation method proposed in this paper, the Yinma River Basin (a tributary of the Songhua River), which flows through Changchun City, Jilin Province, China, is taken as an example. The river not only escorts the sustainable development of the regional economy but also poses a threat to the water safety of residents and the water quality of the Songhua River. The study area is located in the temperate continental monsoon climate zone, with an average annual temperature of 5.7 °C and an average annual precipitation of 642.9 mm. The terrain is high in the south and low in the north, and the altitude of most areas is 260–430 m (Zhang et al., 2012a; Yan et al., 2020). Lu et al., (2011) preserved the water samples according to the "technical regulations for the preservation and Management of water quality samples" in the People's Republic of China, and the concentrations of the measured water quality indicators followed the relevant standards in the Chinese government's "analytical methods for water and wastewater monitoring", and provided the annual average of monitoring indicators from 2001 to 2007. Therefore, this study selected eight biochemical indicators (i.e., ammonia nitrogen (NH_3-H), total nitrogen (TN), total phosphorus (TP), chemical oxygen demand (COD), five-day biochemical oxygen demand (BOD_5), dissolved oxygen (DO), potassium permanganate index(PPI), density of fecal coliform (DFC)) (Tang et al., 2009; Zhang et al., 2012b; Yan et al., 2020), to construct a water quality evaluation index system, and selected two monitoring points (S_1 and S_2) located in the basin as the evaluation objects (Fig. 2). According to national standards (MEP (Ministry of Environmental Protection P.R. China) (2002)), the corresponding evaluation criteria are divided into five levels (Table 2).

4. Results

4.1. Sample generation and its weight determination

Considering the uncertainty of the sampling process to the measured data, the water quality index data identified in section 3 needs to be sampled with the MC method for stochastic simulation. Fig. 3 shows the random distribution of the selected eight water quality parameters for sampling point S_1. As can be seen from Fig. 3, the blue line indicates the random samples generated by 1000 iterations of the selected parameters. The randomly generated samples based on the normal distribution reflect the uncertainty of the measured data. Fig. 4 shows the weights of the selected water quality indicators in this study, where the weights are calculated by using CRITIC method. For the weight distribution of the eight indicators, the highest weight of X_2 is 0.231, while the lowest weight of X_1 is 0.02. The distribution of weights of other indicators lies in the range of 0.057–0.188.

4.2. Identification of water quality level

According to the method described in Section 2.3 and the randomly generated data based on the MC method, we take a sample of the sampling point S_1 as an example to introduce the calculation process of the development method. The values of the eight water quality indicators of this sample are 8.078 mg/L(DO), 11.466 mg/L(COD), 3.793 mg/L(PPI), 2.687 mg/L(BOD_5), 0.462 mg/L (NH_3-N), 1.159 mg/L (TN), 0.049 mg/L

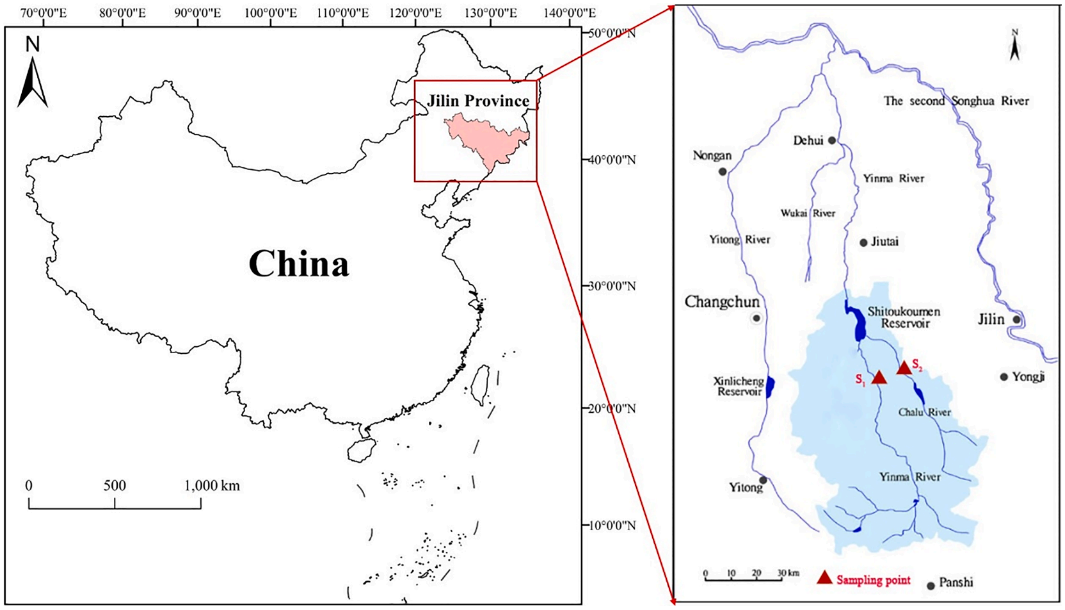

Fig. 2. Location of the study area.

Table 2
Classification criteria for selected indicators (MEP, 2002).

Index (mg/L)	Classification Criteria				
	I	II	III	IV	V
DO (X_1)	7.5	6	5	3	2
COD (X_2)	15	15	20	30	40
PPI (X_3)	2	4	6	10	15
BOD_5 (X_4)	3	3	4	6	10
NH_3-N (X_5)	0.15	0.5	1	1.5	2.0
TN (X_6)	0.2	0.5	1.0	1.5	2.0
TP (X_7)	0.01	0.025	0.05	0.100	0.200
DFC (X_8)	200	2000	10,000	20,000	40,000

(TP) and 2621.9 mg/L (DFC) respectively. Based on Eqs. (7) – (9), we determine the S_i and the R_i (Table 3). In order to obtain the Q_i of the sampling point, we calculate it by Equation (10). The results are shown in Table 3. From Table 3 that C_{Si} = [0.000, 0.144, 0.379, 0.665, 0.999]. Based on the Eqs. (11) – (12), Q_i = [0.000,0.444,0.556,0.000,0.000] can be obtained. Finally, according to Eq. (14), the water quality grade of the sampling point is 2.556, which is divided into level III compared to the water quality standard (Table 1).

Based on the 1000 sample data sets generated in Section 4.1, the water quality of sampling points can be obtained by repeating the above process. Finally, the distribution of water quality evaluation values is used to determine the water quality class of the sampling points. Fig. 5 (the red dashed line indicates the dividing line between water quality level II and level III) shows the distribution of water quality grades for S_1 and S_2 after 1000 iterations. The final grade obtained for water quality is determined by the sample distribution. If the water quality distribution of the samples in this study is higher in one grade than in the other grades, the water quality situation in the study area can be considered to belong to this grade. From Fig. 5, the water quality distribution of S_1 and S_2 is mainly concentrated in the range of 2.5–2.8, which shows that within the five levels classified (Table 1), the highest percentage of grade III (2.5–3.5) in the classified grade. Therefore, the sampling sites S_1 and S_2 should be identified as grade III. However, in some cases (e.g., when the water quality distribution of samples is not so clearly distributed between classes), it is difficult to guide practice, i.e., watershed managers cannot directly discern water quality classes directly from Fig. 5. Therefore, this paper uses a box plot with Histogram (Fig. 6) to show the distribution of water quality grade in the study area. From the histogram in Fig. 6, it can be seen that the water quality grade of the two sampling points S_1 and S_2 is level III, which will help the river basin managers to determine the water quality status in order to carry out water quality restoration work. In addition, Fig. 6 also shows the water quality grade distribution of two sampling points, S_1 and S_2 in the study area in the form of a box plot. It can be seen that the mean values of the two sampling points are higher than 2.5 and the maximum value is within the range of grade III (2.5–3.5) determined in this study. Therefore, it is reasonable to define the water quality grades of the two sampling sites S_1 and S_2 in the study area as Grade III, which is consistent with the assessment of the actual situation (Lu et al., 2011; Li et al., 2018).

4.3. Correlation analysis

A correlation analysis is used for assessing the relationship between input factors and water quality assessment results. Fig. 7 shows the outcomes of the correlation analysis. Samples of these influencing factors are obtained by the MC method. The relationship between the influencing factors and the evaluation outcomes of different sampling points is different. In the sampling point S_1, the top three absolute values of influencing factors are X6 > X3 > X5; for sampling point S_2, the absolute value of the top three factors is X6 > X5 > X3. This shows that these three factors affect the water quality of the study area. This is mainly due to the low effective utilization rate of pesticides and fertilizers in the study area. The organic matter components contained in the cultivated soil and the residues of pesticides and fertilizers enter the river through leaching and dissolution, as well as the discharge of domestic sewage (Zhang et al., 2012a), resulting in the increase of organic matter content in rivers (Wang et al., 2022). Additionally, Fig. 4 shows that these three factors have higher weights in the evaluation process. Therefore, X6 (TN), X3 (PPI) and X5 (NH_3-N) became the main influencing factors of water quality in this area. The results obtained are consistent with some studies (Tang et al., 2009; Zhang et al., 2012b; Yan et al., 2020).

During the study period, the water quality level of the two selected sampling points was at level III. Our results show that TN, PPI and NH_3-N affect the water quality of the study area. Therefore, Relevant measures for restoring water quality are to (1) strictly control the non-point source pollution of farmland and reduce the direct discharge of

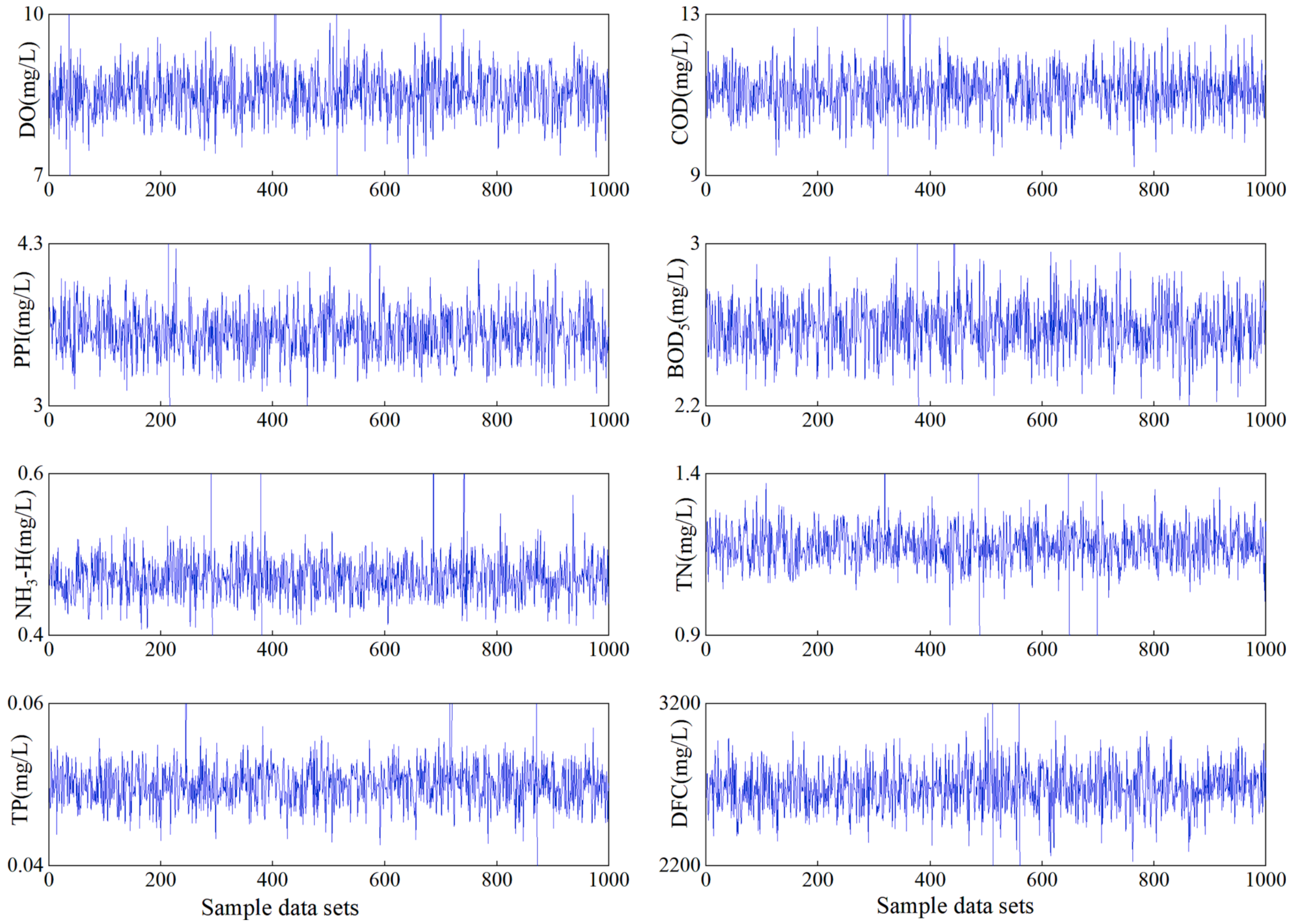

Fig. 3. Random generation of water quality index data based on MC method.

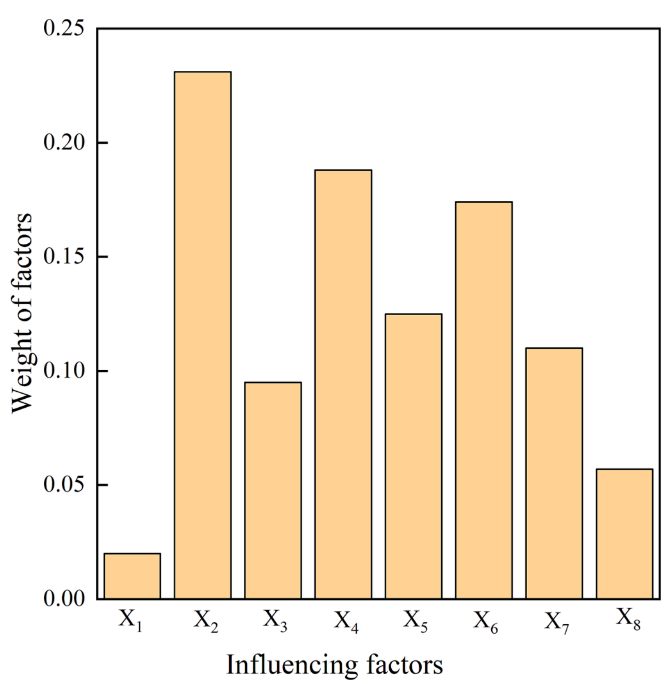

Fig. 4. Weight of selected water quality indicators.

Table 3
S_i, R_i, Q_i values of sampling points and water quality standards.

	Sampling point	I	II	III	IV	V
S_i	0.132	0.000	0.090	0.272	0.546	0.908
R_i	0.071	0.000	0.038	0.093	0.148	0.203
$Q_{i(\lambda=0.5)}$	0.248	0.000	0.144	0.379	0.665	0.999

Table 4
Results of Normality Test.

Index (mg/L)	S_1			S_2		
	W	P	Normality	W	P	Normality
DO	0.998	0.56	Normal	0.999	0.97	Normal
COD	0.997	0.25	Normal	0.998	0.72	Normal
PPI	0.999	0.71	Normal	0.998	0.64	Normal
BOD_5	0.997	0.16	Normal	0.998	0.31	Normal
NH_3-N	0.999	0.87	Normal	0.997	0.11	Normal
TN	0.997	0.13	Normal	0.998	0.71	Normal
TP	0.998	0.70	Normal	0.998	0.46	Normal
DFC	0.997	0.16	Normal	0.998	0.77	Normal

pollutants into the river; (2) strengthen the supervision of coastal sewage discharge, and accelerate the construction of urban sewage facilities; (3) enhance the functions of water resources management department.

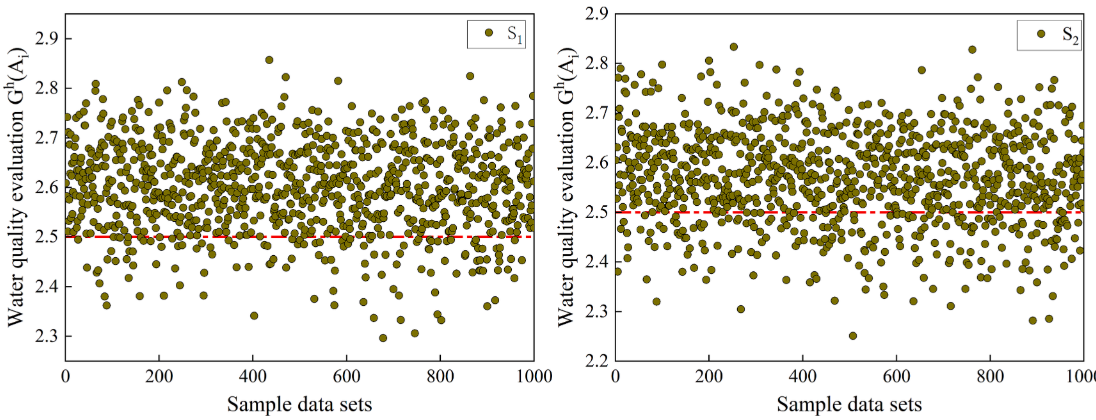

Fig. 5. Scatter plot of water quality distribution of S_1 and S_2.

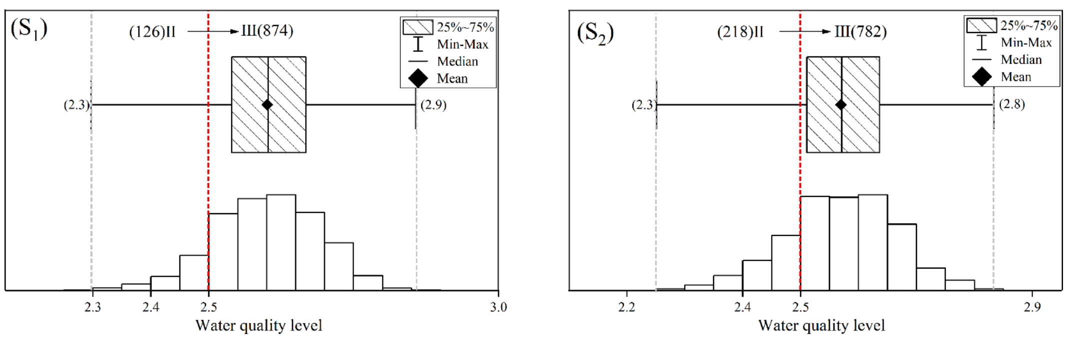

Fig. 6. Box Plot with Histogram about water quality level of S_1 and S_2. (Note: the right side of the red dotted line is level III and the left side is level II).

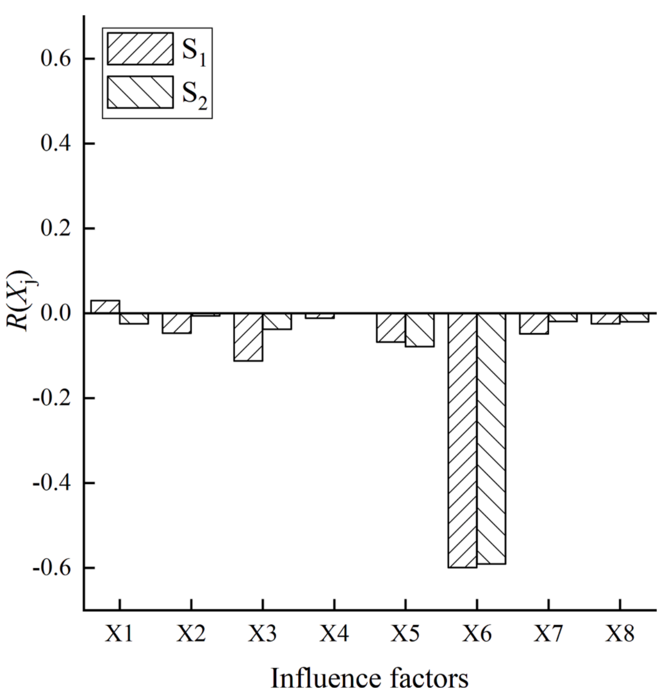

Fig. 7. PCC values of histograms in S_1 and S_2.

5. Discussions

5.1. Sensitivity analysis

In the evaluation, different λ values of will affect the evaluation results. Therefore, on the basis of the measured data (rather than simulated data generated from MC), this study first examined the degree of change in water quality evaluation results under different λ values (including $\lambda_1 = 0.1, \lambda_2 = 0.2, \ldots, \lambda_9 = 0.9$). It can be seen from Fig. 8 that for the two sampling points (S_1 and S_2), when λ is within the range of [0.1,0.5], their water quality grade remains unchanged, which is III level, which is in line with the actual water quality situation. This shows that in the current value range of λ, the water quality of the two

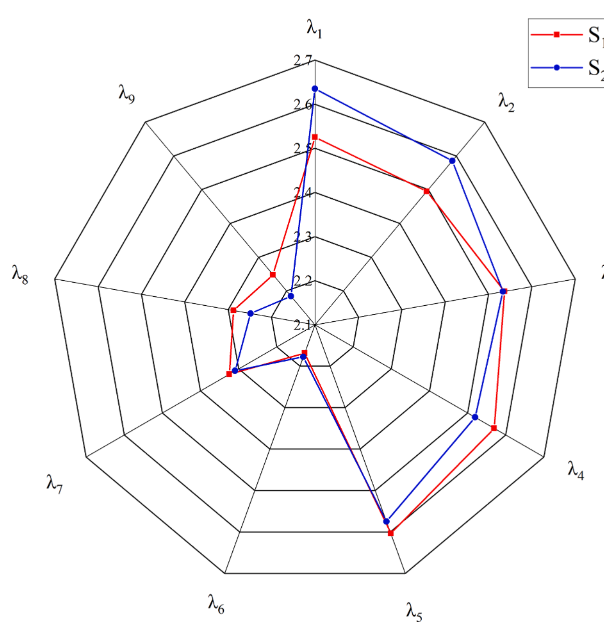

Fig. 8. Assessment results in different λ.

sampling points is highly consistent with the maximum group effect and the minimum individual regret. On the other hand, when λ is greater than 0.5, the water quality grade of the two sampling points changes to II level, which is not consistent with the actual water quality. This indicates that focusing on the smallest individual regret makes the evaluation level to shift from III to II level.

On the other hand, for the influence of different λ values on the assessment results based on the measured values, this study takes the sampling point S_1 as an example to further study the influence of different λ values on the proposed method by setting λ to 0.1, 0.3, 0.5, 0.7 and 0.9. From Fig. 9 and Fig. 6 (for λ = 0.5) that when λ is set within the range of [0.1–0.5], the water quality results can match actual level. When the λ values are 0.1,0.3 and 0.5, the frequency of water quality evaluation results obtained is higher than 58 %, and increases with the increase of λ value. However, when the value of λ is greater than 0.5, such as 0.7 and 0.9, the water quality level has gradually shifted from the III level to the II level, until λ is 0.9, the level is completely in the II level. Therefore, in order to obtain an accurate level, the λ value should be set to [0.1–0.5].

Finally, we compare the evaluation results of Fig. 8 (based on the measured data) and Fig. 9 (based on the MC method). It is evident that the assessment outcomes of the two are basically the same. However, the results of Fig. 8 do not reflect the effect of sampling errors on the evaluation results. For example, when λ = 0.1, the evaluation sampling point S_1 is III level. Fig. 9 shows the frequency distribution of water quality classes under different λ. For example, when λ = 0.1, the frequency distribution of S_1 at the II and III levels can be seen, and the frequency of the latter is greater than that of the former, so it is judged that S_1 belongs to the third level. This comparison indicates that the assessment results through the MC method can overcome the uncertainty caused by measurement errors, thus improving the diagnostic ability of water quality level.

5.2. Effect of probability distribution on water quality results

Various probability distribution types can be used in MC random simulation of data. Therefore, for comparison, we chose uniform distribution (upper and lower limits set at 5%) and normal distribution to characterize the uncertainty of measurement data to explore the effects of various probability distributions on water quality assessment outcomes, taking S_1 as an example. Fig. 10 shows that the distribution frequency (874) of water quality assessment results based on normal distribution is slightly clearer than the distribution frequency (869) of water quality assessment results using uniform distribution, but the difference is not obvious. However, from the distribution curve in Fig. 10 (red represents normal distribution, blue represents uniform distribution), the curve based on normal distribution can attain more robust assessment outcomes than the curve based on uniform distribution. This is due to the uniform distribution that the probability of values obtained within the water quality grade range is the same. The normal distribution is given a larger probability around its average and a smaller

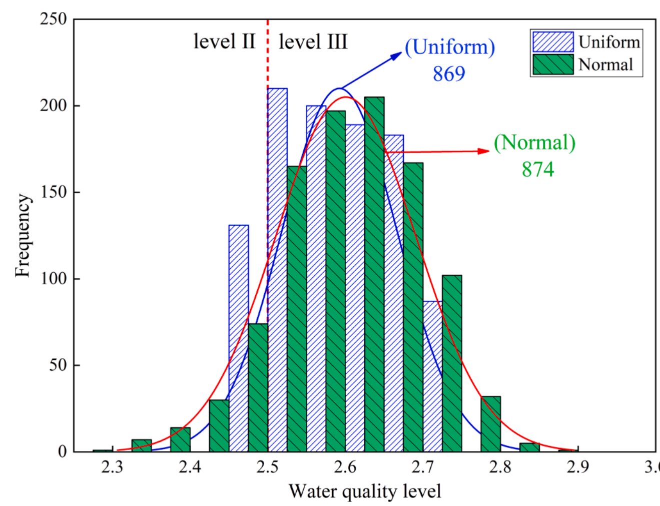

Fig. 10. Water quality level distribution of S_1 based on different probabilities.

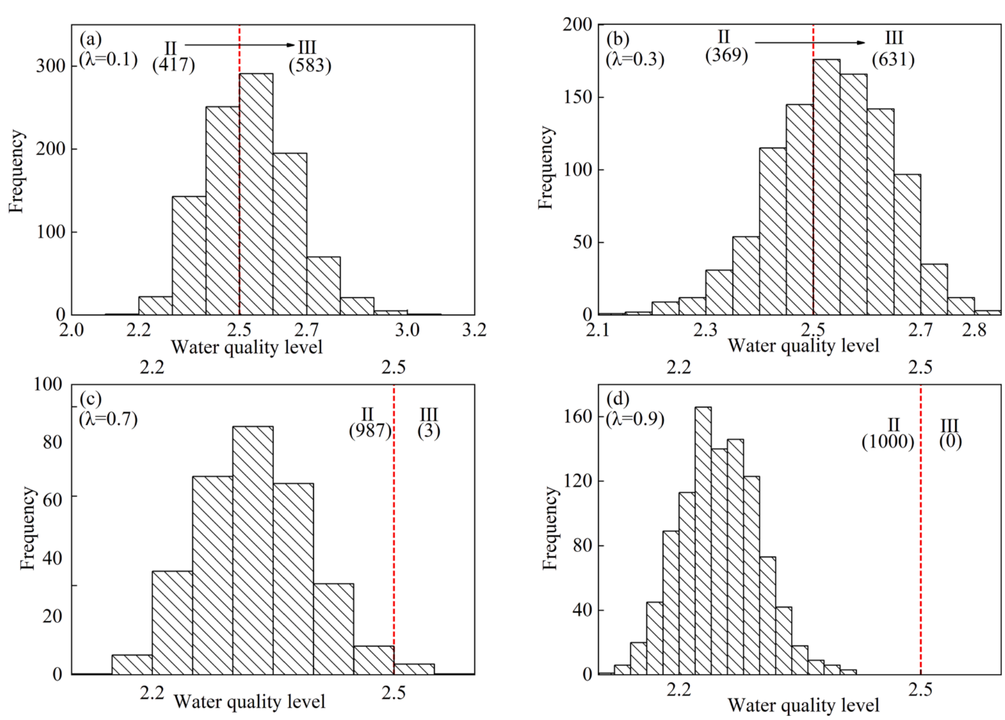

Fig. 9. Histogram about water quality level of S_1 under different λ with developed method. (Note: the right side of the red dotted line is level III and the left side is level II).

probability at the end of the curve. When evaluating water quality in a changing environment, evaluators are increasingly aware that they will not be able to evaluate with traditional methods and must consider uncertainties in the assessment process. Thus, to obtain credible assessment outcomes in a changing environment, it is necessary to use a decreasing probability distribution curve from the middle to the tail of both sides, such as a normal distribution (Zhu et al., 2019).

5.3. Application range and future research fields

The basic characteristics of water quality conditions can be described by constructing an assessment index system considering the actual conditions of the study area and then using an evaluation model to diagnose them. Previous studies have mainly explored the applicability of different models in the water quality evaluation process (Wang et al., 2020; Ruan et al., 2021; Tang et al., 2022). Here we propose a hybrid evaluation model framework. Although the rivers in northeast China were studied as a case study, the methods used in our framework have been widely used in various regions of the world (Golfam et al., 2019; Seifi et al., 2020; Ruan et al., 2021). Therefore, our proposed framework for hybrid water quality assessment models is widely applicable. In addition, the main pollutants in the study area are TN, PPI and NH_3-N. The excessive content of these indicators will cause eutrophication of water bodies, causing rapid reproduction of algae and other plankton in aquatic ecosystems, a decrease in dissolved oxygen in water bodies, and a large number of deaths of fish and other organisms. The deterioration of water quality poses a serious threat to human and animal health. As a result, important ecosystem services are lost, including fisheries, tourism and water supply. This shows that managers need to pay more attention to these water quality indicators and promote the improvement of water quality in the water ecosystem to restore the service function of the water ecosystem, so as to achieve a win-win situation for the social economy and water environment in the study area (Li et al., 2022a; Hagy et al., 2022).

In general, the proposed framework has two main advantages. First, we use the MC method to overcome the uncertainty due to measurement errors. The method makes full use of the raw data information and can reduce the effect of measurement error on the evaluation outcomes, so that the water quality class can be determined according to the distribution of the evaluation results (Fig. 6). Although the integrated evaluation model is constructed by fusing several models (Li et al., 2017; Yan et al., 2017; Egbueri, 2022), a simple hybrid model (hybrid MC and VIKOR) is used in this study. Secondly, we identified the main factors affecting the study area by considering the correlation between influencing factors and water quality evaluation results, which can provide a reference basis for water quality restoration by watershed managers. Previous studies on water quality assessment only qualitatively analyzed the causes of the assessment results (Wong and Hu, 2014; Guo et al., 2020; Ruan et al., 2021). The correlation between the evaluation results and the influencing factors has rarely been explored from a quantitative perspective.

Although our proposed method can effectively reduce the uncertainty of river water quality assessment results, it also has some limitations. For instance, it is challenging to establish a common evaluation indicator system for water quality to identify the rivers' water quality in different regions. This is because different types (or different regions) of rivers are affected by different natural and human factors (Yao et al., 2021). In the future, it needs to further investigate the water quality of rivers across various regions and seek to establish a common evaluation index system. In addition, we use the national water quality grade (MEP (Ministry of Environmental Protection P.R. China) (2002)) to determine the river's water pollution status. Although this level is conservative and commonly used, it may also lead to some differences between the evaluation results and the local river water quality status. In addition, the method developed in this study needs to be applied to water quality assessment studies of rivers around the world to enhance the feasibility of the water quality assessment method. Moreover, this study does not directly consider the relationship between water quality changes and ecosystem services, which has been used to study the value assessment of water quality-related services. Further research should study the value evaluation of different regional scales and consider the synergy between services.

6. Conclusions

Aiming at the uncertainty generated in the collection process of water quality data, a robust surface water quality assessment model was developed, and the proposed model was verified using the tributaries of the Songhuajiang River. The main conclusions are as follows:

(1) The water quality evaluation model developed in this study combines MC, CRITIC, VIKOR and membership methods, which can make up for the shortcomings of traditional evaluation, expand the ability of existing methods, and provide a potential method for river water quality evaluation under uncertain environment.
(2) The developed method was used for evaluating the water quality of a Songhua River tributary. It can be found that the grade of the two sampling points is III level, which is consistent with the actual situation, indicating that the developed method can effectively reflect the water quality of the study area.
(3) The Pearson correlation coefficient was used to identify the influencing factors of water quality in the study area, namely TN, PPI and NH_3-N, respectively, which can provide control objectives and directions for managers to restore water ecosystem functions. In addition, the study of different λ using sensitivity coefficient shows that λ should be set in the range of [0.1, 0.5] in order to match the water quality status, which can help water quality managers to reliably assess the water quality status.

Although these findings help us understand the water quality of the study area and provide a reference for water quality restoration. However, future research will: (i) use water quality data from different regions to enhance the feasibility of the developed evaluation method; (ii) consider the influence of other uncertain factors (e.g., indicator weight) on the evaluation results;(iii) consider the different value dimensions of ecosystem services and their dependence on social needs, further analysis of the interaction between water quality changes and ecosystem services under the synergy between different services is needed to better guide managers.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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