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Eutrophication assessment and bloom control strategy of water body based on fuzzy rough set algorithm under the development of urban landscape lakes and reservoirs

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ABSTRACT

Currently, most urban landscape lakes and reservoirs are facing severe water eutrophication and rampant water blooms. To improve water quality environment, a water eutrophication evaluation model and a water bloom strategy model based on fuzzy rough set algorithm are proposed in this study. An improved multidimensional normal cloud model was used to correct assessment uncertainty of water bloom eutrophication. And this experiment used fuzzy rough set to improve case-based reasoning technology to improve water bloom strategy accuracy. The average evaluation accuracy of total nitrogen, total phosphorus, chlorophyll-a, turbidity and chemical oxygen demand in 10 lake cases is 91.56%, 90.83%, 93.15%, 91.69% and 92.77%, respectively. The evaluation results of the simultaneous evaluation model are roughly the same as those of water quality testing center, with an accuracy rate of 95.47%. In addition, the average strategy accuracy based on fuzzy rough set algorithm is 92.15%, and the matching degree for lake A case retrieval is 0.1632, indicating a high degree of similarity. In summary, water eutrophication evaluation model and water bloom strategy model based on fuzzy rough set algorithm proposed by this research institute can accurately evaluate the water eutrophication situation of lakes. And it can accurately search for similar cases of water bloom outbreaks, providing reference value for water body protection and management.

Keywords: Water eutrophication; Water bloom; Multidimensional normal cloud; Case-based reasoning; Fuzzy rough set algorithm

1. Introduction

Water is life source and ecosystem foundation. However, with population growing, the accelerated industrialization and urbanization development, water pollution (WP) and water bloom (WB) have become increasingly serious, which has brought great harm to ecological environment and human health [1,2]. To protect ecological environment and human health, effective governance methods need to be taken to reduce industrial and agricultural pollution from the source and strengthen waste management [3]. Therefore, how to prevent and effectively manage WP and WB has become a hot issue in water resource protection. This study was optimized on the basis of multidimensional normal cloud model (MNCM), utilizing analytical hierarchy process (AHP) and criterial importance through inter criteria correlation (CRITIC) to optimize model parameters. They proposed a water augmentation (WE) evaluation model based on MNCM and a WB strategy model based on fuzzy rough set algorithm (FRS). Through research results, it is hoped that the evaluation model's accuracy and the matching WB strategy model's accuracy can be improved,

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providing enterprises with more accurate and efficient water body evaluation plans and governance strategies. The research innovation points mainly include two points. The first point is to optimize the uncertainty problem in parameter correction evaluation based on MNCM. The second point is to improve FRS, and optimize this method of obtaining node weights with key formula in complex network, and apply it to case matching. This study consists of four parts in total. Firstly, it is an analysis and description of recent relevant literature. Next is the design of WE evaluation and WB strategy based on FRS. Then there is the research results' effectiveness analysis and validation. The final part is a research content summary [4].

2. Related works

Water is the most basic necessity for human survival. But as economy develops rapidly, water body is increasingly polluted, and the most noticeable issue is WE. Therefore, it has become an inevitable trend to evaluate WE situation and trends and to explore sustainable water management methods based on these evaluation results. Chen et al. [5] proposed a new method for adjusting indicator weights using the AHP entropy weight method to address the problems in fuzzy comprehensive evaluation. Hanfeng Lake is greatly affected by total nitrogen (TN) and total phosphorus (TP), and is moderately to slightly eutrophication. Yu and Gan [6] proposed a three-dimensional physical biogeochemistry model to solve the problem of hypoxia caused by eutrophication in Pearl River Estuary. Oyster culture can alleviate eutrophication and hypoxia. Zhang et al. [7] proposed a model based on PCA and MLR to evaluate the water quality of Gaoyou Lake. TLI of Gaoyou Lake shows a significant increase trend, and the lake surface is in a mild to moderate eutrophic state. Yuan et al. [8] put forward a eutrophication assessment method using micro Fourier-transform infrared spectroscopy to explore the microplastics pollution in inland freshwater lakes. Among the 24 monitoring points, the proportion of severe, moderate, mild eutrophication and moderate eutrophication points in the total sampling points is 8.33%, 58.33%, 29.17% and 4.17%, respectively, and the main pollutant is TN. To evaluate the pollution situation of Baiyang Lake, Liu et al. [9] proposed a method to analyze the temporal and spatial pollution characteristics of Baiyang Lake and its influencing factors in combination with historical monitoring data. Baiyang Lake water is eutrophication. Among 26 sampling points, mild eutrophication accounts for 16.53%, moderate eutrophication accounts for 6.20%, and severe eutrophication accounts for 20.17%.

As a targeted decision analysis tool, AHP can provide reliable and effective decision support in complex and ever-changing decision-making environments, and is widely used in various fields. Alosta et al. [10] proposed an integrated AHP-RAPSI method to optimize the optimal location of Emergency Medical Services (EMS) Centers in Libya. This road network is the best choice for locating EMS Centers. Hossain and Thakur [11] proposed a hybrid multi criteria decision-making tool based on fuzzy AHP to determine key factors for implementing Industry 4.0 in HCSC. HC logistics management is the top priority factor for implementing Industry 4.0, followed by integrated HCSC and sustainable HCSC practices. Valentino et al. [12] proposed an AHP based paper session support system to achieve objective scoring in paper experimental systems. This support system makes objective evaluation a definitive scoring system and can assist examiners in providing the best advice. Hanim and Rahmadoni [13] proposed a method of using AHP to determine lecturers to address the issue of staffing or facilitating qualified instructors acquisition on campus. This method can effectively obtain qualified instructors. Dar et al. [14] proposed a method using geographic information systems and AHP to delineate potential groundwater zones in the Kashmir Valley. The study area includes five different potential groundwater recharge areas, including excellent (28.97%), good (19.99%), medium (21.70%), poor (27.16%) and very poor (2.15%).

In summary, many scholars have conducted research on WE evaluation methods and AHP application from various aspects at present. However, due to water body condition's uncertainty and variability, these evaluation methods have limitations. Therefore, this study utilizes AHP and CRITIC to optimize MNCM parameters to solve the randomness and fuzziness problems in evaluation process, and introduces FRS optimized case retrieval technology for selecting WB methods.

3. Design of WE evaluation and WB strategy based on FRS

This section focuses on the design principles of WE evaluation and WB strategy based on FRS. It mainly includes using AHP-CRITIC method to improve MNCM weights, while using FRS to solve the uncertainty in case matching.

3.1. Evaluation, governance methods, and system framework design of WE

Human society development has made WP problem increasingly serious, bringing great impacts to the environment and ecosystems [15]. WE is a manifestation of WP, which refers to the excessive nutrients content such as nitrogen and phosphorus in water, leading to aquatic ecosystem's balance disruption. Generally speaking, WE is caused by excessive emissions of organic matter, nitrogen, phosphorus, and other substances generated by activities such as urbanization, fertilizers, and livestock breeding. At present, the comprehensive evaluation methods of WE mainly include index evaluation method (IEM), fuzzy evaluation method, set pair analysis method, interval analysis method, etc. in Fig. 1.

In Fig. 1 IEM quantifies each indicator weight by establishing a water body indicator system. And it weighted each indicator score to obtain a comprehensive evaluation index, thereby achieving a comprehensive WE evaluation. However, when using IEM, due to the introduction of different method parameters, it is easy to cause water quality evaluation results to deviate far from the actual situation. The fuzzy evaluation method is based on WE fuzzy description, utilizing the concepts and operations of fuzzy mathematics to obtain evaluation results. However, factors such as membership function setting, synthesis algorithm selection, and evaluation level setting during the evaluation process can all affect evaluation results. Therefore, in

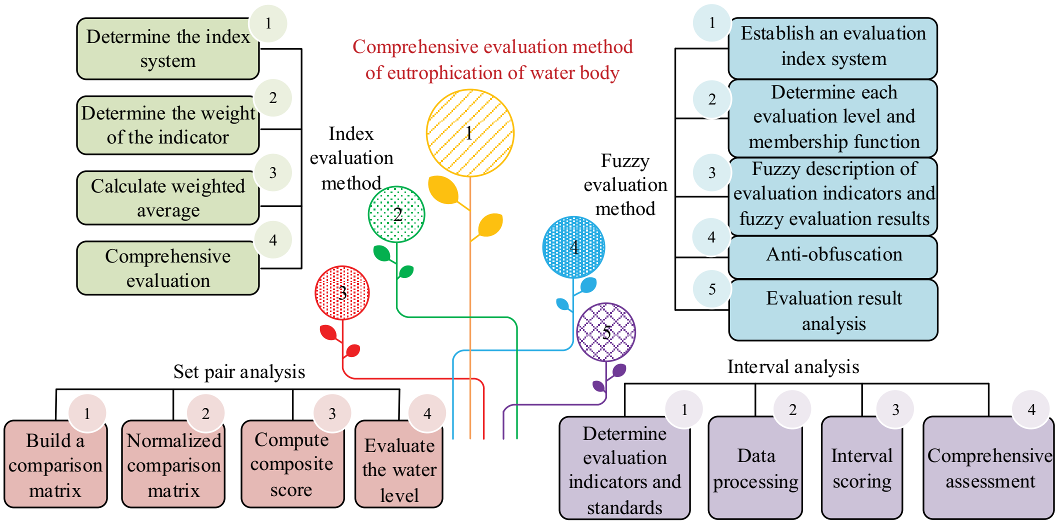


Fig. 1. Comprehensive evaluation method and steps of water body eutrophication.

practical applications, it is necessary to fully consider how these factors affect evaluation results. The set pair analysis method is to construct a comparison matrix and normalize eutrophication by comparing two evaluation indicators. WE level was evaluated by calculating the comprehensive score of each water sample. The interval analysis method first determines evaluation indicators and standards. Then, each indicator in water body was measured and indicator concentration was divided according to the evaluation criteria. In the final experiment, methods such as arithmetic mean and weighted mean were used to calculate each indicator's average scores, to comprehensively evaluate WE degree.

WB governance is a key issue in improving WP. Currently, WB governance measures mainly include physical control, chemical control, and biological control. Physical control methods refer to changing water environment's physical conditions to achieve WB [16]. Generally, it includes mechanical decontamination, aeration treatment, sedimentation treatment, turbine treatment, and artificial fluidized bed treatment. However, it should be noted that different physical control methods are applicable to different types of water bodies and WBs. Therefore, when treating WB, it is necessary to comprehensively consider water body characteristics and choose appropriate physical control methods to achieve the best treatment effect. Chemical control method refers to the use of chemicals to kill or control algae in water body, so as to inhibit algae growth. Common chemicals include copper sulfate, peroxide, copper(II) chloride, etc. Although chemical control methods have the function of quickly controlling WB, it is necessary to select control agents and doses based on the type and degree of WB. And it is necessary to follow safety and environmental protection principles to avoid negative impacts on water environment and ecosystem. This biological control method is to prevent WB growth by introducing specific species such as water shrimp, snails, and turtles that prey on WB plants. In the practical application, three measures have their own advantages and disadvantages, and application scope is also different. Usually, a combination of several measures is used to achieve better governance effects.

On the basis of WE evaluation methods and WB measures, the study proposes to improve MNCM to evaluate WE, and proposes a Decision model based on FRS to govern WB. Fig. 2 shows the overall framework of this system.

In Fig. 2 the study first investigates WE evaluation methods and WB governance measures. Then, based on this, a WE evaluation model based on improved MNCM and a WB model based on improved FRS are established. This study uses AHP and CRITIC to optimize model parameters, combined with evaluation results to construct a governance decision-making ontology model, and uses rule reasoning and FRS to retrieve cases and applies them to WB. In summary, complete the evaluation, governance methods, and system framework design of WE.

3.2. Design of WE evaluation model based on improved MNCM

In WE evaluation, there are many factors that can affect water quality status. Based on empirical analysis of 22 large and medium-sized lakes, this study selected chlorophyll-a (Chl-a), TP, TN, turbidity (SD), and chemical oxygen demand (COD) as the main influencing factors. WE reasons are diverse, and water environment is complex and variable. Currently, there is no unified evaluation standard. Eutrophication assessment criteria of Chinese lakes were used as assessment criteria. Due to WE fuzziness and randomness, MNCM was used in this study to determine water sample quality status [17]. MNCM processes data in a form that conforms to the normal cloud (NC) distribution, and better describes data uncertainty and fuzziness through random variables representation, better reflecting data characteristics and regularity in real scenarios. Using MNCM to evaluate WE, this experiment first defined U as cloud model domain, and Eq. (1) represents the mapping of U on closed interval [0,1].

$$\mathrm{CT}(x): U \rightarrow [0,1] \tag{1}$$

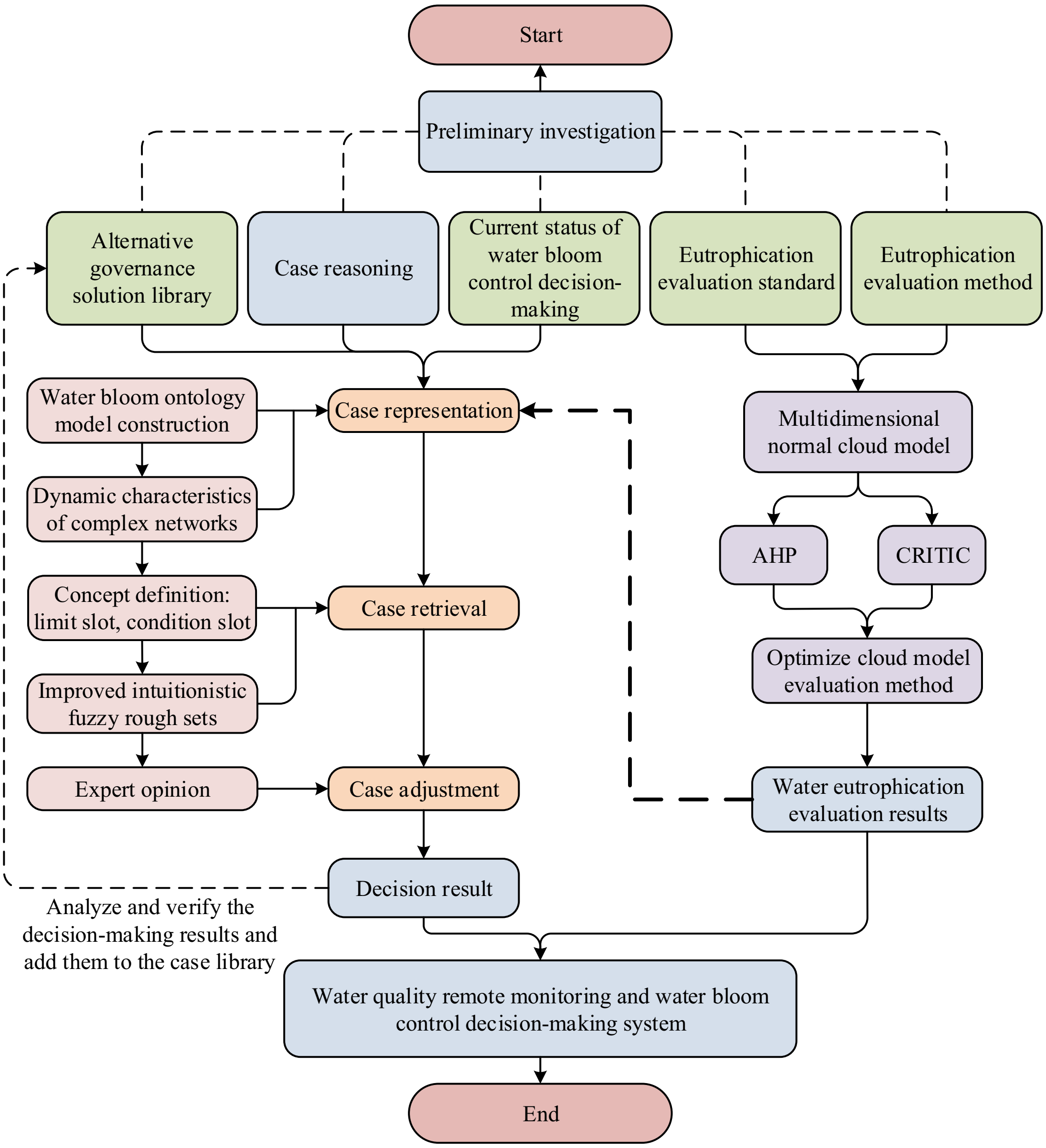


Fig. 2. Overall frame design of the system.

where x is a random number that follows a specific law. $\mathrm{CT}(x)$ is a mapping and is a non-constant value. T is a fuzzy subset on U. The distribution of $\mathrm{CT}(x)$ on U is the membership cloud of T in Eq. (2).

$$\forall x \in U, x \rightarrow \mathrm{CT}(x) \tag{2}$$

$\forall x \in U, CT(x)$ refers to a large number of cloud droplets, which are normally distributed. When U extends from one-dimensional to multidimensional, MNCM can be obtained. The language in evaluation is fuzzy, therefore it is defined as a fuzzy subset in cloud model. The transformation between qualitative and quantitative concepts was achieved through the uncertainty transformation model of language values. The uncertainty is obtained by combining fuzziness and randomness in cloud models. Cloud droplet uncertainty reflects the contribution of certain cloud droplet conditions. Cloud droplet number reflects data distribution, thus obtaining one-dimensional normal random cloud distribution in Eq. (3).

$$\begin{cases} P_i = R_1(\mathrm{En},\mathrm{He}) \\ \mu_{i=}e^{-\frac{1}{2}\left(\frac{x-\mathrm{Ex}}{P_i}\right)^2} \end{cases} \tag{3}$$

where R_1 is a normal random distribution function. μ_i is certainty degree. Ex, En, and He represent expectation, entropy, and superentropy, respectively. The cloud droplets in one-dimensional model are represented as drop(x_i, μ_i),

i = 1, 2, 3, …, N. Fig. 3 shows the one-dimensional NC distribution.
where Ex, En, and He are important digital features in one-dimensional NC models. When one-dimensional NC model's U extends from one-dimensional to two-dimensional, a two-dimensional NC model is obtained. Eq. (4) represents random cloud distribution.

$$\begin{cases} \left(P_{xi}, P_{yi}\right) = R_2\left(\text{Enx}, \text{Eny}, \text{Hex}, \text{Hey}\right) \\ \mu_i = e^{-\frac{1}{2}\left(\frac{x_i - \text{Ex}}{P_i}\right)^2 - \frac{1}{2}\left(\frac{y_i - \text{Ey}}{P_i}\right)^2} \end{cases} \quad (4)$$

where R_2 is a two-dimensional random function. Ex, Ey are two-dimensional expectations. Enx, Eny are two-dimensional entropy. Hex, Hey are two-dimensional hyperentropy. Two-dimensional model's cloud droplets are represented as drop(x_i, y_i, μ_i), i = 1, 2, 3, …, N. Fig. 4 shows the two-dimensional NC distribution.

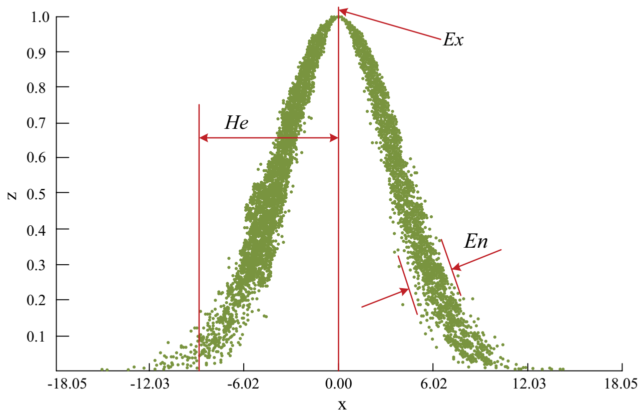


Fig. 3. One-dimensional normal cloud model.

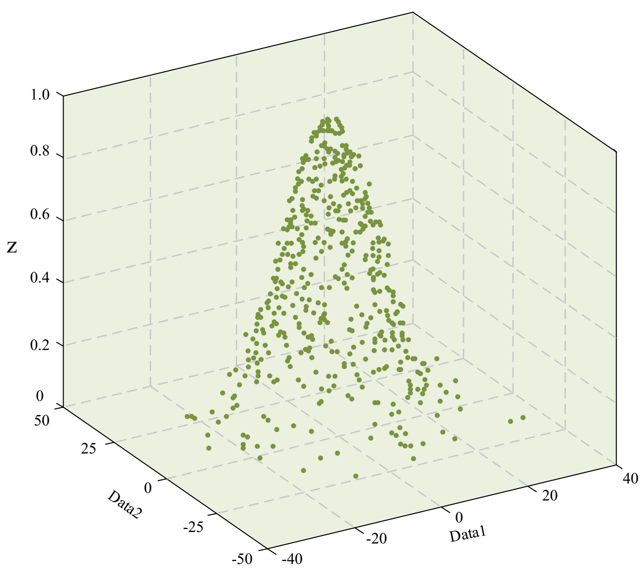


Fig. 4. 2D normal cloud model.

Extending one-dimensional cloud model to two-dimensional cloud model can be further extended to a multidimensional cloud model, similar in principle to one-dimensional and two-dimensional cloud models. In WE evaluation, multiple indicators are involved, so the multi-dimensional cloud model is selected as the evaluation model. Eq. (5) is certainty degree.

$$\mu\left(X\left(X_1, X_2, \ldots, X_m\right)\right) = \exp\left[-\sum_{j=1}^{m} w_j \times \frac{1}{2}\left(\frac{x_j - \text{Ex}_j}{\text{En}_j}\right)^2\right], j = 1, 2, \ldots, m \quad (5)$$

where w_j is weight. Multidimensional cloud model's digital features still include Ex, En, and He. MNCM is generated by a cloud model generator using modular software in Fig. 5. where a weight w_j will be added to cloud model uncertainty formula, which can be determined by combining AHP and CRITIC methods. AHP decomposes a problem into multiple levels, calculates each weight level, and obtains the final decision result [18]. When solving weights using AHP, the first step is to use a hierarchical structure model combined with expert opinions to construct a relative importance judgment matrix, and then calculate weight vector based on AHP. Eq. (6) calculates the product of row data.

$$h_i : h_i = \prod_{j=1}^{n} x_{ij}\left(i, j = 1, 2, \ldots, n\right) \quad (6)$$

where i, j are any water quality indicators, x_{ij} is matrix element, and h_i is the product of row data. Weight w_j is obtained based on the square root of h_i in Eq. (7).

$$\bar{w}_j : \bar{w}_j = \sqrt[n]{h_i} \quad (7)$$

The weight $w = [\bar{w}_1, \bar{w}_2, \ldots, \bar{w}_n]^T$ is normalized using Eq. (8).

$$w_j = \frac{\bar{w}_j}{\sum_{i=1}^{n} \bar{w}_j} \quad (8)$$

After obtaining weight vector, consistency needs to be judged before it can be applied in actual calculation. Consistency index (CI) is first calculated for consistency judgment in Eq. (9).

$$\text{CI} = \frac{\left(\eta_{\max} - n\right)}{\left(n - 1\right)} \quad (9)$$

where $\eta_{\max}$ is the maximum eigenvalue. n is the matrix order. CI = 0 has complete consistency. CI is greater, n consistency is more severe. Subsequently, consistency ratio (CR) is calculated in Eq. (10).

$$\text{CR} = \frac{\text{CI}}{\text{RI}} \quad (10)$$

where RI is an empirical statistic. If CR < 0.1, it is considered that judgment matrix consistency is acceptable, otherwise

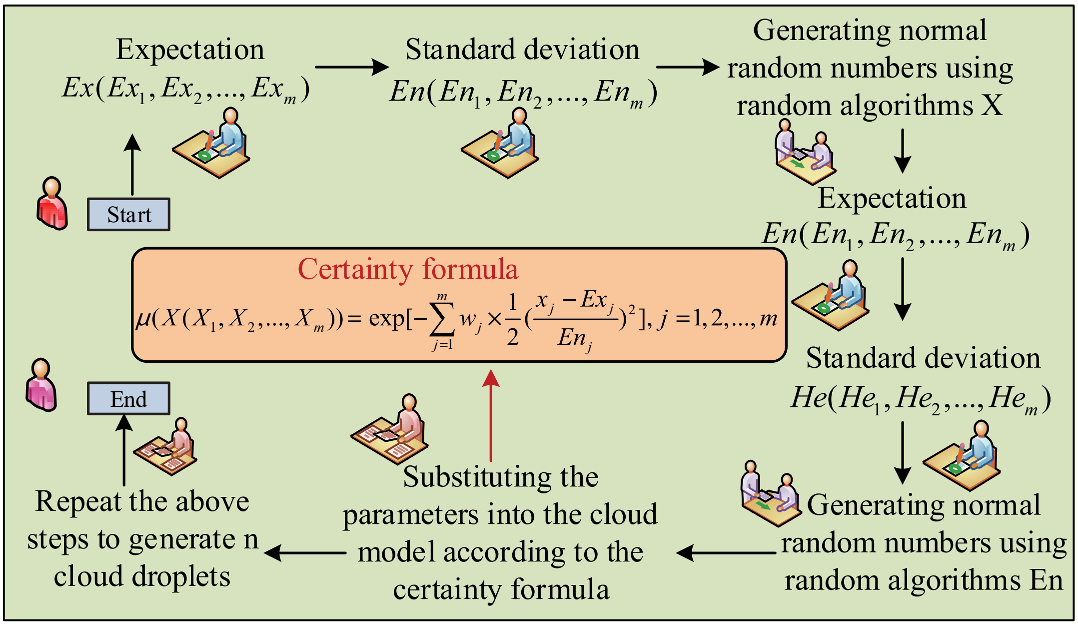


Fig. 5. Generation steps of cloud model generator.

it needs to be corrected. CRITIC method determines indicators' objective weights based on two basic concepts by comparing intensity and evaluation indicators' conflict. The comparative strength represents difference magnitude in values between different evaluation schemes for same indicator, expressed in standard deviation. The standard deviation is larger, the greater the difference in values between each scheme. The conflict between evaluation indicators refers to the correlation between indicators. If there is a strong positive correlation between two indicators, it indicates that their conflict is relatively low. CRITIC method was used to calculate weights in Eq. (11).

$$\begin{cases} w_j = \dfrac{m_j}{\sum_{j=1}^{n} m_j} \\ m_j = \delta_j \sum_{j=1}^{n} \left(1 - r_{ij}\right), \left(j = 1,2,...,m\right) \end{cases} \tag{11}$$

where δ_j is indicator volatility. r_{ij} is the correlation between the i-th and j-th indicators. m_j is indicator information quantity. Due to single method's shortcomings for calculating weights, this study used a comprehensive weight calculation formula to determine WE evaluation indicators weights in Eq. (12).

$$w_j = \frac{w_{\text{AHP}_j} w_{\text{CRITIC}_j}}{\sum_{j=1}^{m} w_{\text{AHP}_j} w_{\text{CRITIC}_j}} \tag{12}$$

Study combined AHP and CRITIC methods to optimize MNCM's weight parameters, thereby obtaining WE evaluation indicators weights. In summary, a WE evaluation model design based on improved MNCM has been completed.

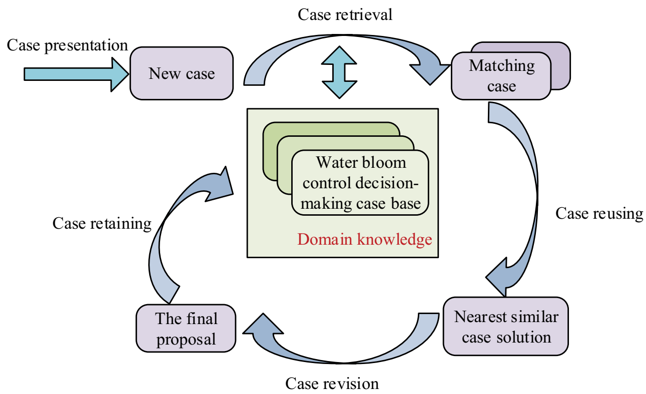


Fig. 6. Case-reasoning model.

3.3. Design of WB strategy model based on improved FRS

To maintain nature balance, WB, as a common phenomenon of WP, its governance strategy is essential. This study adopts the improved Case based reasoning (CBR) method to make WB decisions. CBR solves new problems by existing cases or experiences. It can fully utilize existing knowledge and experience, thereby improving problem solving's efficiency and accuracy. Usually, it includes four steps: case representation, retrieval, correction, and learning. The commonly used model R^4 is the inference model in Fig. 6.

The case representation in Fig. 6 adopts a structured form to express case content. Ontology description language is one form that has advantages of clarity, formalization, and sharability. This study selects ontology description language to represent cases of WB decision-making. Case retrieval can affect reasoning process efficiency. Research has used rule-based reasoning to preliminarily screen cases to reduce computational complexity, while using FES to calculate similarity for case matching. Due to natural environment rapidly changing, case retrieval cannot be guaranteed to be identical with actual situation. Therefore, this study adopts the expert opinion method to revise search cases to meet practical use. Case study refers to the process of re storing the final solution and effects in a case library for future reference and use. Basic case study methods are used to document application cases. This study first establishes a universal ontology model for WB decision-making. Decision ontology is defined as a five-tuple model that includes concepts, instances, constraints, relationships, and rules. Concept refers to the concept related to WB decision-making in water environment governance, including eutrophication and surface properties. Instance is a collection of instances in water environment governance. Constraints are constraints related to the field of water environment governance. Relationship refers to the relationship between concepts, concepts, and attributes in water environment governance. Rules are the rules that should be followed in water environment governance. This study used Prote'ge' ontology tools to OWL encode ontology concepts and construct an ontology model to improve subsequent CBR efficiency. Based on the ontology model, case representation is used to construct a WB case library. This case library collects WB cases of lakes in recent years, as well as a summary of WB outbreaks, environmental factors, and governance situations.

The research further constructs a model of dynamic association characteristics of complex network to describe external WB relationship to achieve case retrieval. The related water environment concepts are represented by key nodes in complex network, and the relationships between concepts are represented by lines between nodes. Due to indicator's different nature, indicator scope in WB decision-making is divided into total network and sub network. Total network is governance case's comprehensive attribute, and the sub network is attribute subdivision in Fig. 7.

The i-th attribute of total network in Fig. 7 is V_i, and the g-th attribute of i-th sub network is V_{ig}. In this study, a criticality evaluation matrix was constructed to determine the key nodes in complex network, so as to achieve optimization and rate node weights, and further reflect the impact of various factors on WB process. When determining weight, it is necessary to clarify five key feature parameters, one is entry degree ε_i^+, and ε_i^+ is other nodes number in network that have edges connected to that node. The second is egress degree ε_i^+, and ε_i^- is nodes number on the edges that exit from that node in network. The third is the node degree ε_i. ε_i is the sum of ε_i^+ and ε_i^+, representing the number of nodes connected to this node. The fourth is the shortest distance d_{ij}. d_{ij} is the path length between two nodes that passes through the least number of edges, commonly used to measure network reliability and stability. The fifth is network efficiency E. E is the difficulty of information transmission in network. The E is higher, the network performance is better, as calculated in Eq. (13).

$$E = \frac{1}{n(n-1)} \sum_{i \neq j} \frac{1}{d_{ij}} \tag{13}$$

where n represents nodes number. Eq. (14) is the network efficiency calculation for a single node.

$$S_k = \frac{1}{n} \sum_{i=1, i \neq j}^{n} \frac{1}{d_{ki}} \tag{14}$$

where d_{ki} is the shortest distance between nodes i,k. The S_k is larger, the network efficiency is higher and these nodes are more important. In WB process, the interaction between attributes has a causal relationship. Therefore, this study combines the dual requirements of global and local, and further improves the node key formula itself to obtain the optimized node key in Eq. (15).

$$C_i = I_i \times \sum_{j-1, j \neq i}^{n} \delta_{ij} \left(\varepsilon_j^{\varepsilon_j^- / \varepsilon_j} \right)^2 I_j / < k >^2 \tag{15}$$

where I_i and I_j represent information content importance of nodes i and j themselves. δ_{ij} allocates parameters for contributions. $<k>^2$ is the average node degree. Complex network weight is calculated by normalizing node key matrix in Eq. (16).

$$w_j = \frac{C_i}{\sum_{i=1}^{n} C_i} \tag{16}$$

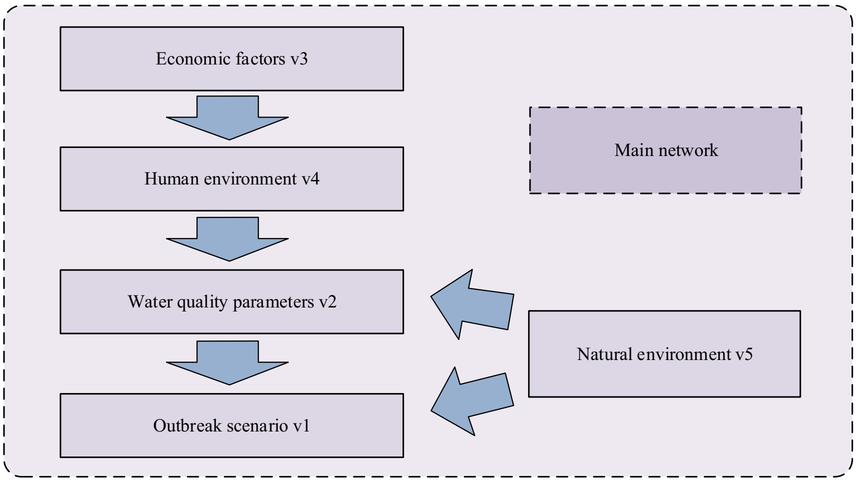
From this, the total network and each sub network's attribute weights are calculated. Then FRS method is introduced to deal with water environment's uncertainty and fuzziness [19]. Assuming that R is a fuzzy rough set, the upper approximation in $\forall Y \in R$ is Y^+, and the lower approximation is Y^-, then Eq. (17) is the fuzzy rough set G in R.

$$G = \left\{ \left\langle \varphi_{G^+}(y), \varphi_{G^-}(y), \varphi_{G^+}(y), \rho_{G^-}(y), \rho_{G^+}(y) \right\rangle \middle| \forall y \in Y \right\} \tag{17}$$

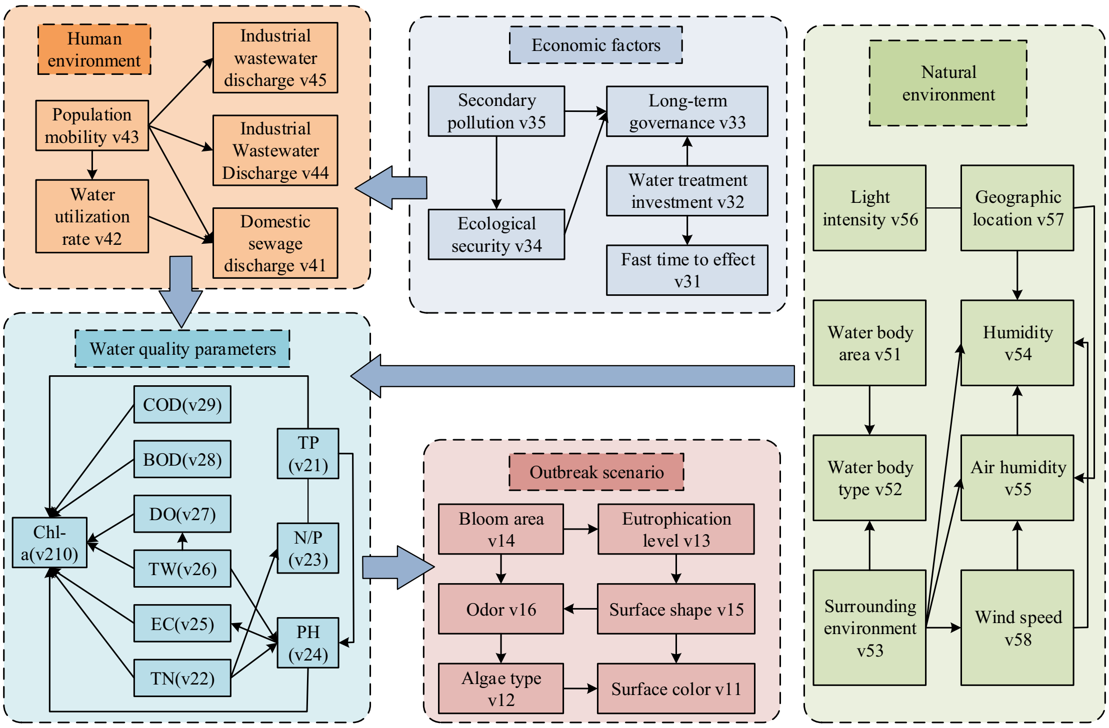
where φ_{G^-} and φ_{G^+} are the lower approximation and upper approximation membership functions of G, respectively. φ_{G^-} represents the degree to which attributes have a negative impact on WB decision-making process. φ_{G^-} represents the potential negative impact of attributes on WB process. ρ_{G^-} and ρ_{G^+} are the lower approximation and upper approximation non membership functions of G, respectively. ρ_{G^-} is the degree to which attribute has a positive impact on WB decision-making process. ρ_{G^+} represents the possible positive impact of attributes on WB process. The modified intuitionistic index $\pi_G(y)$ of the intuitionistic fuzzy rough set G is a measure of y's hesitation towards G. This study introduces exponential operator α_G to modify $\pi_G(y)$ to weaken uncertainty impact on two fuzzy rough sets' similarity [20]. In actual WB process, there is a problem of attribute missing. In the case matching process, the contribution degree is proposed to combine attribute's weight to calculate matching case value. Eq. (18) is the calculation of comprehensive contribution degree.

$$Z_{pq} = \sum_{i=1}^{m} f_i \times \left(\sum_{j=1}^{n} \left(f_{ij} \times M_{ij} \right) \right) \tag{18}$$

where Z_{pq} represents the contribution of cases p and q that are similar. f_i is the importance level of i-th node in total



(a)General network representation of water bloom control decision-making



(b)Water bloom control decision-making sub-network representation

Fig. 7. Total network and sub-network representation of water bloom control decision-making.

network. f_{ij} is the importance level of j-th node in i-th sub-network. M_{ij} is the contribution of j-th node in i-th sub network. When matching cases, the contribution of governance attributes to case matching degree is calculated by this attribute similarity value. If attribute value can be obtained, the attribute contribution to matching degree can be calculated based on similarity. If attribute value is missing, the contribution is 0, which means it cannot have any impact on decision result. In this study, cases' comprehensive contribution values were compared, and the highest value was selected as the matching case. Further comparison was made between the maximum comprehensive contribution and the matching threshold of 0.5. $Z_{pq} > 0.5$ indicates that the case is available, and $Z_{pq} < 0.5$ indicates that there are no matching cases. In summary, WB strategy model design based on FRS has been completed.

4. Performance analysis of WE evaluation and WB strategy based on FRS

To verify the feasibility and effectiveness of WE evaluation and WB strategy based on FRS, this section focuses on designing validation experiments of evaluation models on 10 lakes. The contents of TN, TP, Chl-a, SD, and

COD were tested, and WB strategy model's feasibility was verified using lake A as an example.

4.1. Performance analysis of WE evaluation model

To verify WE evaluation model feasibility based on improved MNCM proposed by research institute, 10 representative medium and large lakes were selected for model validation experiments. These lakes include Qionghai Lake, Erhai Lake, Bosten Lake, Yuqiao Reservoir, Dianshan Lake, West Lake, Poyang Lake, Chaohu Lake, Gantang Lake and Luhu Lake. The study used the proposed AHP-CRITIC model to test TP and TN contents of 10 lakes in spring, summer, autumn, and winter seasons, and compared them with actual values.

Fig. 8a and b show 10 lakes' TN and TP contents in four seasons, respectively. Compared with the actual TN and TP contents in lakes, the average TN content testing accuracy in four seasons of AHP-CRITIC model is 91.56%, and the average TP content testing accuracy is 90.83%. AHP-CRITIC model has a high accuracy and good usability in evaluating lake water quality. This study further used AHP-CRITIC model to test Chl-a, SD, and COD contents of 10 lakes in four seasons, and compared them with actual values.

Fig. 9a and b show 10 lakes' Chl-a, SD, and COD contents in four seasons. Compared with the actual Chl-a, SD, and COD contents in lakes, the average Chl-a content testing accuracy of AHP-CRITIC model in four seasons is 93.15%. The average SD content testing accuracy is 91.69%, and the average COD content testing accuracy is 92.77%. The AHP-CRITIC model proposed by this research institute has a high accuracy in evaluating lake water quality, which is not significantly different from the actual results. These five water quality evaluation indicators selected for this study are reasonable. The improved AHP-CRITIC model and the existing single factor evaluation (SFE), comprehensive evaluation method (CEM), MNCM were further used to evaluate the eutrophication of 10 lakes, and the evaluation results were compared.

Table 1 shows the eutrophication assessment comparison results of four methods for 10 lakes. Compared with other three methods, AHP-CRITIC model's evaluation results are roughly the same, indicating the WE evaluation applicability. And AHP-CRITIC model can balance the impact of all water quality indicators on water body state, resulting in more comprehensive and complete results. The surveyed lakes' water quality evaluation indicators vary greatly between different periods, and the lakes nutritional status is also constantly changing. To objectively reflect the nutritional status and changing characteristics of 10 lakes, this study conducted 5 samples of water bodies from 10 lakes. 50 data obtained in this experiment will be used as separate samples. AHP-CRITIC model proposed by this research institute and MNCM were used for evaluation testing, and these evaluation results were compared with those of water quality testing center at the corresponding time.

In Fig. 10, AHP-CRITIC and MNCM methods' eutrophication grade assessment results of 50 water samples are compared with water quality testing center's results. The comparison shows that these evaluation results of AHP-CRITIC MNCM method and water quality testing center are roughly the same, with an accuracy rate of 95.47%, while MNCM method has an accuracy rate of 90.65%. Comparative experiments have shown that studying and improving MNCM weight parameters is effective. Water quality evaluation accuracy has been improved by 4.82%, which can

Table 1
Comparison of eutrophication evaluation results

Lake name	AHP-CRITIC	SFE	CEM	MNCM
Qionghai lake	IV	V	IV	IV
Erhai lake	III	IV	III	III
Bosten lake	IV	IV	IV	IV
Yuqiao reservoir	IV	V	IV	IV
Dianshan lake	IV	V	V	V
West lake	VI	VI	VI	VI
Poyang lake	VI	VI	VI	VI
Chaohu lake	V	VI	V	V
Gantang lake	VI	V	VI	VI
Luhu lake	IV	V	V	V

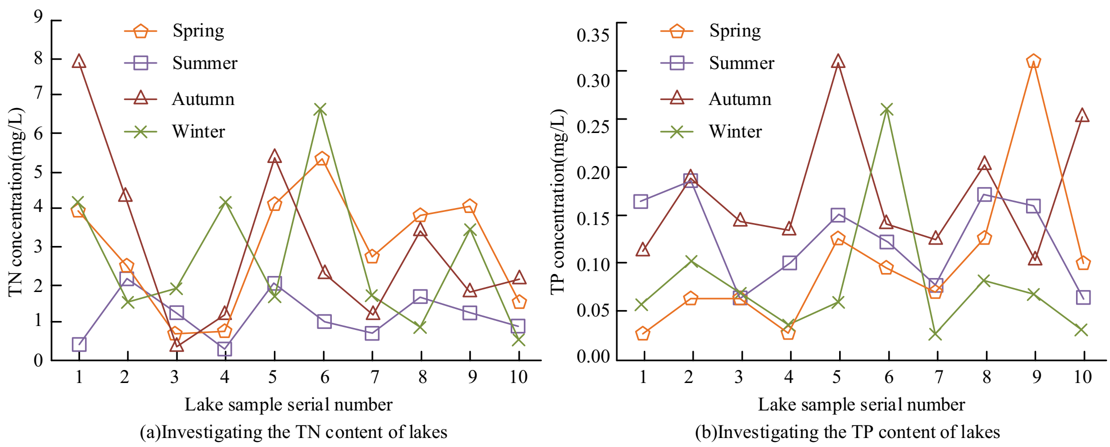


Fig. 8. (a) Total nitrogen and (b) total phosphorus contents in four seasons of 10 investigated lakes.

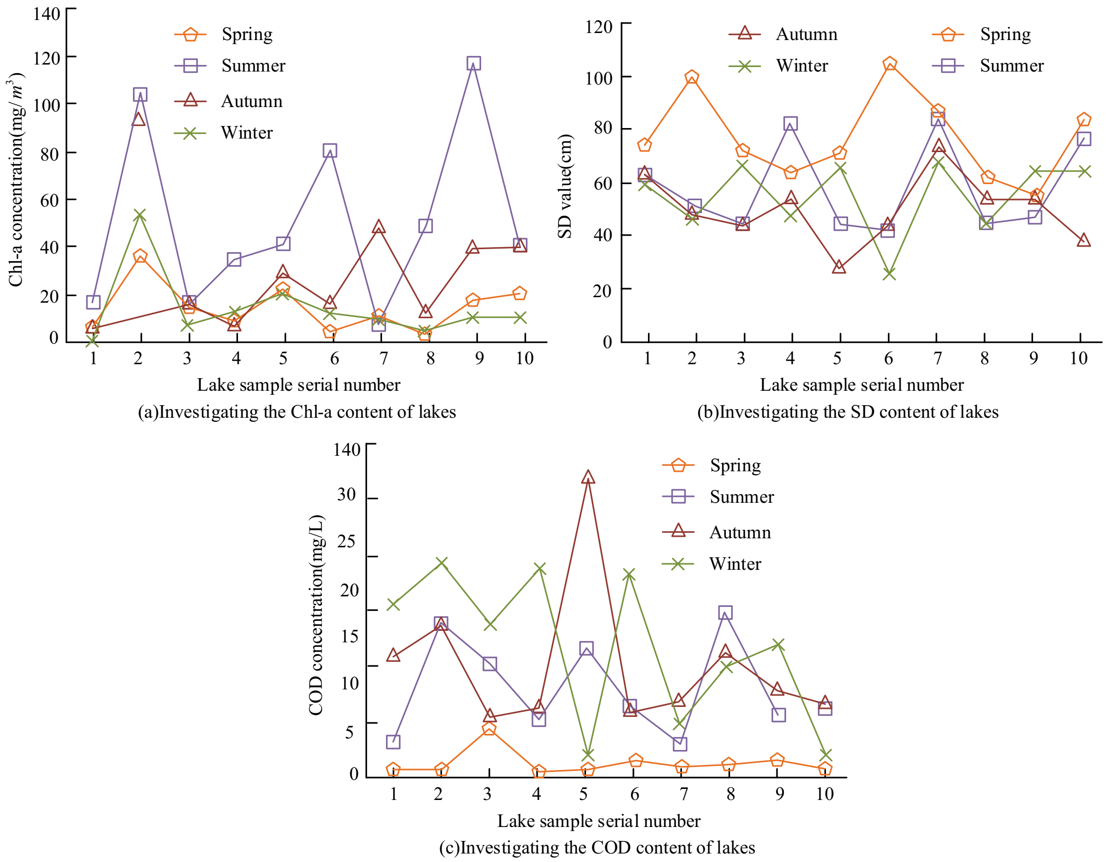


Fig. 9. Contents of (a) chlorophyll-a, (b) turbidity and (c) chemical oxygen demand in 10 lakes were investigated in four seasons.

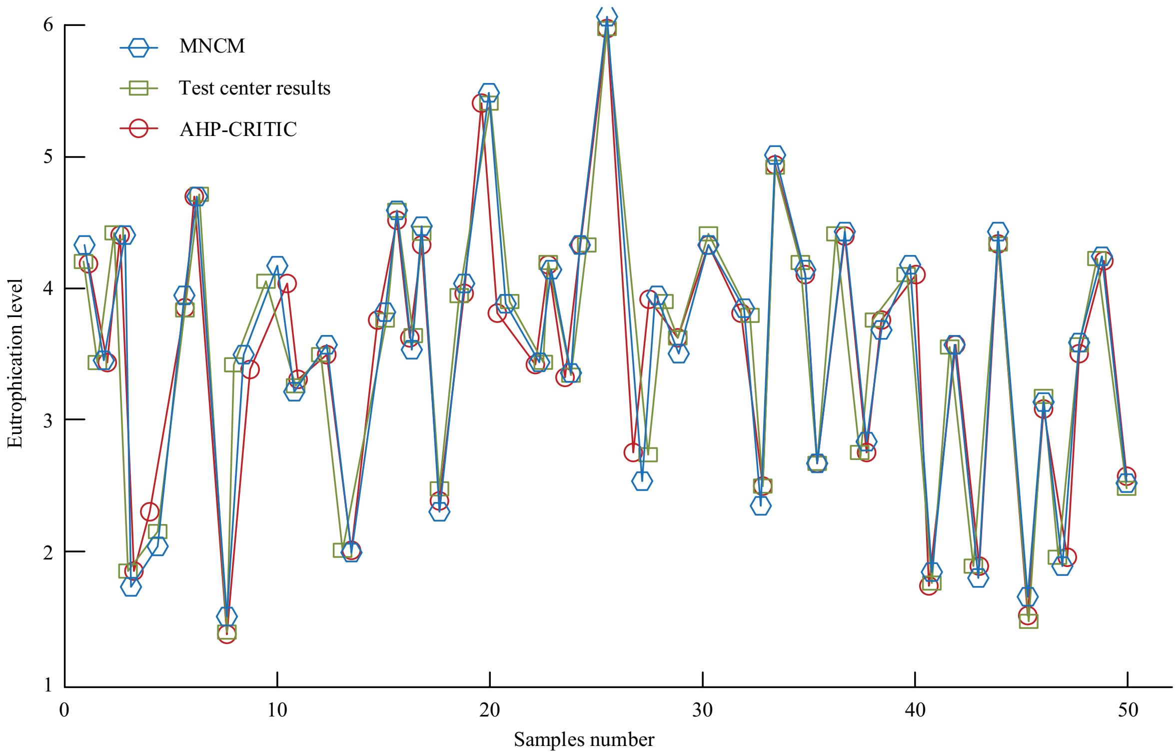


Fig. 10. Evaluation model evaluation results comparison.

obtain more reasonable water quality evaluation results. In addition, AHP-CRITIC method used in this study calculates weights using water quality data measured on site. The weights calculated for different water quality data are different. This greatly expands model applicability and further enhances evaluation model's practical value in water quality evaluation applications.

4.2. Performance analysis of water management strategy model

To verify WB strategy model's applicability based on FRS proposed by this research, this study selected WB outbreak case data in lake A in 2016 as experimental data. The governance strategy recorded in case library for lake A is the mechanical algae removal method in physical methods, which has the greatest similarity to WB outbreak situation in lake D. This proposed model was used to match the case and governance methods of lake A, and these results were compared with database.

Fig. 11a shows the similarity matching results of the proposed model between lake A and cases in case library. The similarity between lake D and lake A is 0.953, while its similarity with lake B is 0.863, its similarity with lake C is 0.836, and its similarity with other lakes is lower. In the similarity results, D lake case's WB outbreak situation is the most similar to A lake case, which is consistent with the actual results. This proposed model can accurately retrieve matching cases. Fig. 11b shows governance methods' matching results for a similar case to lake A. These treatment methods similar to those in lake A are mostly mechanical algae removal, with a contribution rate of up to 0.5231. This indicates that the preferred treatment method for lake A is mechanical algae removal, which is consistent with the actual treatment method. To verify the proposed model's effectiveness, this study selected four methods: CBR, vague set multi-objective decision making (VSM), fuzzy Bayesian (FB), and multiple attribute decision making (MA) to rank lake A's WB decision-making. And these ranking results are compared.

Fig. 12 shows the sorting results comparison of lake A's WB strategy using four methods. Among four methods, mechanical algae removal is the best choice. And the proposed method's governance strategy ranking is basically consistent with the ranking results of VSM, FB, and MA. This further proves that the research method's strategy is applicable and effective for WB governance. To further validate

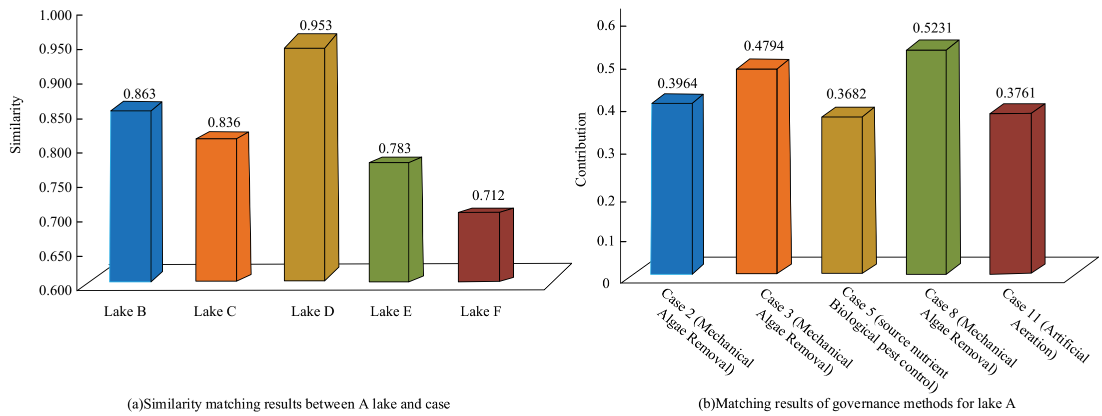


Fig. 11. (a) Lake case and (b) governance outcome matching results.

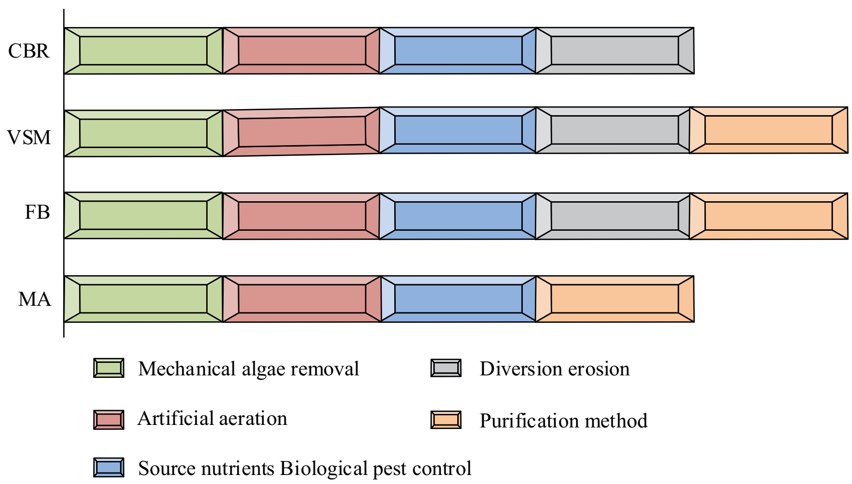


Fig. 12. Comparison of ranking results of four methods for decision-making of water bloom control in lake A.

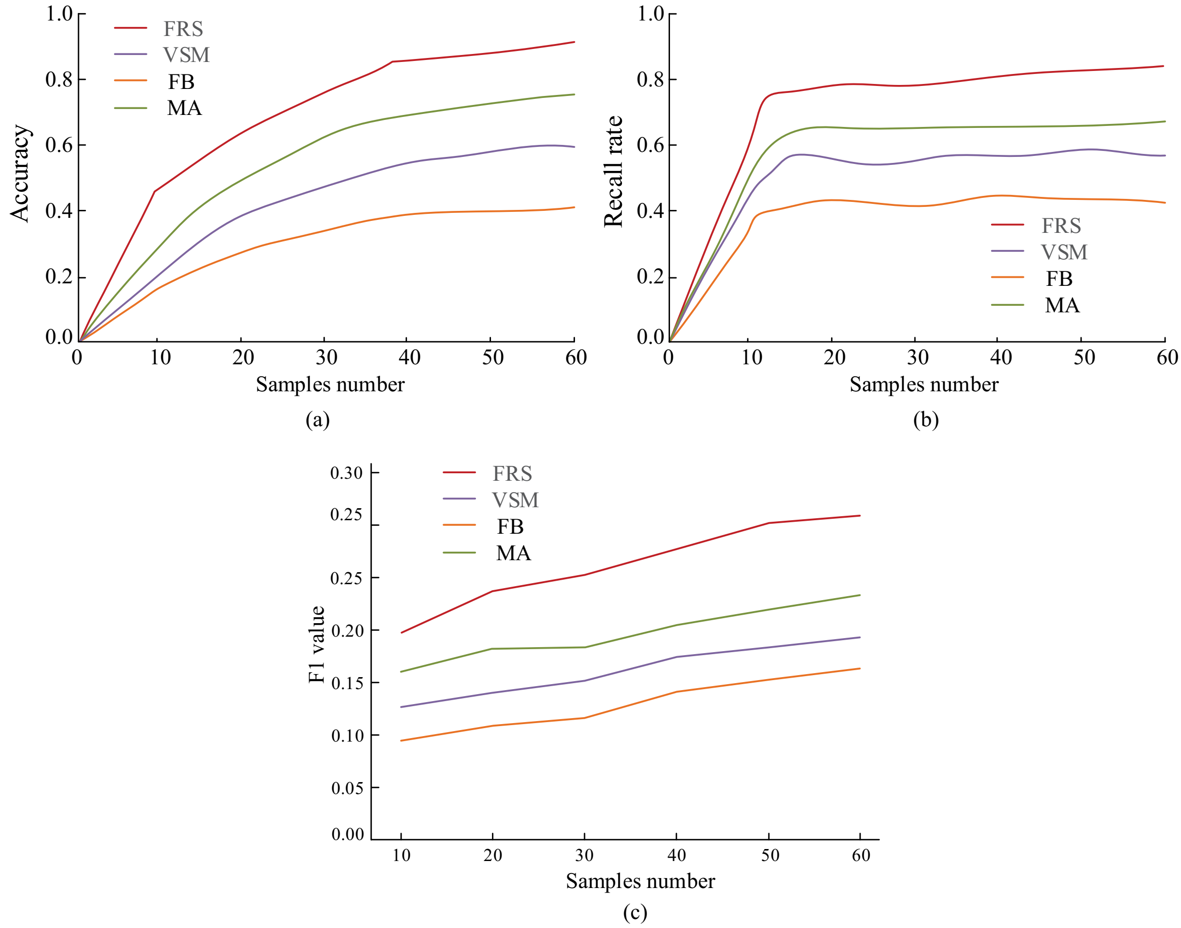


Fig. 13. Comparison of (a) accuracy, (b) recall, and (c) F1 values of the four models.

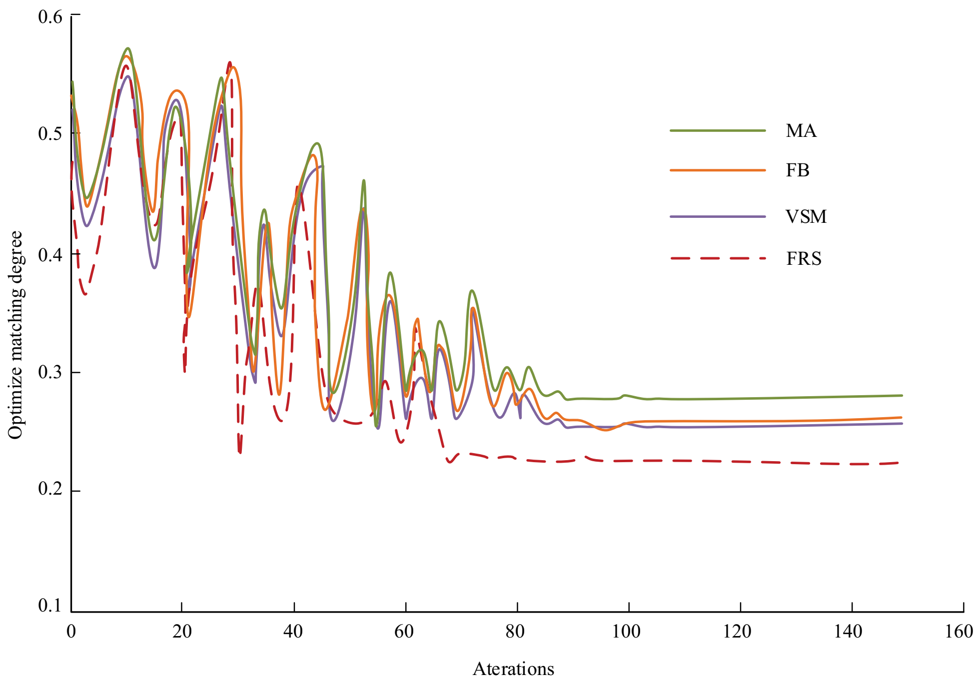


Fig. 14. Comparison of decision-making effects of algal bloom outbreak in lake A.

the proposed model's governance strategy accuracy for WB outbreak, this study selected 10 cases from case library for testing. WB strategy model based on FRS, decision model based on VSM, decision model based on FB and decision model based on MA proposed by the research institute were used for the experiment. Accuracy, recall, and F1 value were selected as performance indicators to compare the test results.

Fig. 13a–c shows the comparison results of accuracy, recall, and F1 values for four models. FRS model proposed by this research performs better in terms of accuracy, recall, and F1 value. Its average accuracy is the highest at 92.15%, VSM's average accuracy is 90.34%, FB's average accuracy is 91.22%, and MA's average accuracy is 89.92%. The proposed model's strategy for WB outbreak is accurate, basically in line with the actual situation, and has good practicality. To further validate the proposed model's decision matching effect, four models were used to test WB outbreak case data matching degree in lake A.

Fig. 14 shows the decision-making effects comparison of four models on WB outbreak in lake A. FRS model's convergence is faster, indicating that the governance strategy solution optimized by FRS has better convergence. The matching degree of FRS model is 0.1632, while the matching degrees of VSM, FB, and MA models are 0.1861, 0.1897, and 0.1923, respectively. The case retrieved by FRS model is more similar to lake A. In summary, the WB strategy model proposed by this research institute based on FRS is closer to target lake's ideal solution and it has higher accuracy.

5. Conclusion

Water is an indispensable resource for human life. To meet people's living and industrial production needs, WP is becoming increasingly serious, and WB phenomenon is also becoming more and more common. When WB phenomenon increasingly severe in urban landscape lakes and reservoirs, research has proposed a WE evaluation model based on improved MNCM and a WB strategy model based on FRS. Compared with the actual content of lakes, AHP-CRITIC evaluation model's average accuracy for TN, TP, Chl-a, SD, and COD content testing results is 91.56%, 90.83%, 93.15%, 91.69%, and 92.77%, respectively. Compared with MNCM evaluation method, AHP-CRITIC evaluation model's evaluation results are roughly the same as water quality testing center, with an accuracy rate of 95.47%. In addition, FRS strategy model's average accuracy is 92.15%. The average accuracy of VSM, FB, and MA were 90.34%, 91.22%, and 89.92%, respectively. In the case retrieval of lake A, FRS model has a matching degree of 0.1632, which is superior to VSM, FB, and MA models. The retrieved cases are more similar to lake A. To sum up, the WE assessment model based on the improved MNCM proposed by the research can accurately assess the Eutrophication of water quality. The WB strategy model proposed in this experiment can accurately match appropriate cases and governance methods based on WB outbreak's actual situation. This can provide reference for relevant departments to protect and manage water bodies. However, there are still shortcomings in this research, as the case library used in this study was manually organized and collected, lacking diversity. Further research can be conducted on enriching case library and accurately describing evaluation language fuzziness.

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