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Improved Entropy-AHP-TOPSIS method in comparison to traditional methods for assessing reclaimed water's impact on river water quality and ecological health

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This study aims to assess the multidimensional impacts of reclaimed water replenishment on river water environments. Taking a specific case study of a riverine reclaimed water supply project from a wastewater treatment plant in Ningbo City, the research focuses on developing a scientific method for assessing the environmental effects of reclaimed water input on surrounding river ecosystems. Through comparative analysis of the strengths and limitations of traditional single-factor method and comprehensive pollution index method, this paper proposes an improved assessment method—Entropy-AHP-TOPSIS (IEATM)—which combines entropy weight method and analytic hierarchy process. The conventional assessment methods often employ simplistic linear processing, frequently neglecting the actual characteristics of negative indicators and interval-type indicators. The IEATM effectively distinguishes and optimizes the treatment of negative and interval-type indicators. The results demonstrate that this method offers significant advantages in assessing river ecological health, effectively avoiding evaluation deviations caused by short-term exceedances of individual indicators. Additionally,

the IEATM clearly reveals the spatial attenuation patterns and seasonal fluctuation characteristics of the reclaimed water replenishment effects. This provides a crucial theoretical foundation for optimizing reclaimed water replenishment strategies and offers practical guidance for segmented water inflow regulation, ecological wetland construction, and the improvement of river ecological monitoring networks.

Keywords: Reclaimed water supplement; Improved Entropy-AHP-TOPSIS method; River ecological health assessment; Management strategies; Evaluation method construction

Highlights：

1. Using negative and interval indicators to refine the Entropy -AHP-TOPSIS method;
2. The model offers clear advantages in comprehensiveness, objectivity and precision;
3. The model reveals the spatial/seasonal variations in reclaimed water replenishment.

Introduction

With the accelerating pace of urbanization and the increasingly severity of water scarcity, reclaimed water has emerged as a vital "secondary water source," playing a pivotal role in alleviating urban ecological water demands [1,2]. In recent years, global efforts, driven by policy guidance and technological innovation, have been actively advancing wastewater resource utilization, with China achieving notable advancements in this field. As a key strategy for mitigating water shortages, reclaimed water has been implemented extensively in numerous cities [3,4]. The influence of reclaimed water on river ecosystems poses multifaceted challenges. On the one hand, reclaimed water provides a valuable supplement to water supplies for rivers and lakes, alleviating water scarcity by reducing reliance on groundwater and natural water sources [5]. This approach contributes to increased water volume, improved hydrodynamic conditions, enhanced reproductive capacity of aquatic organisms, and the preservation of self-purification mechanisms and biodiversity, ultimately promoting aquatic ecological health [6,7]. On the other hand, reclaimed water may also exert direct stress effects on aquatic organisms. Specifically, the nutrients in reclaimed water, such as nitrogen and phosphorus, can easily lead to eutrophication in water bodies [8]. Research has shown that the replenishment of reclaimed water may alter the structure of algal communities in rivers [9]. Furthermore, reclaimed water is conducive to algal growth, and its ecological impact on algae is typically stronger than that on microorganisms [10]. Therefore, constructing a scientifically sound and reasonable water body evaluation method, which comprehensively considers multi-dimensional indicators of water quality and ecological health, is of paramount importance. Such a method would enable precise assessment of the ecological effects of reclaimed water utilization, facilitate the optimization of water resource management strategies, and ensure the safety and sustainability of water environments.

Traditional research on river water quality and ecology has predominantly relied on single-factor evaluation methods, as outlined in the national standard "Environmental Quality Standards for Surface Water" (GB 3838-2002, China), and on the comprehensive pollution index method developed based on this standard. Currently, research on the impact assessment of reclaimed water on river water quality and ecosystems has achieved some progress, yet shortcomings remain in terms of comprehensiveness and systematicness. First and foremost, existing studies predominantly concentrate on the independent analysis of single water quality indicators, thereby failing to elucidate the multi-dimensional composite effects of reclaimed water input on the water environment. For instance, Shi et al. [11] discovered that reclaimed water replenishment significantly enhances dissolved oxygen (DO) levels and zooplankton diversity in rivers. However, their investigation was limited to discrete evaluations of individual indicators, neglecting the synergistic mechanisms between water quality parameters and ecological responses. Similarly, Yan et al. [12] highlighted the potential exacerbation of eutrophication risks by reclaimed water, but their analysis remained centered on chemical indicators such as ammonia nitrogen (NH_3-N) and total phosphorus (TP), without integrating critical ecological metrics like algal biomass and microbial community structure. This oversight results in evaluation outcomes that inadequately capture the comprehensive impact of reclaimed water on ecosystems. Notably, recent endeavors by certain scholars to enhance evaluation systematics through the introduction of multi-attribute decision models have shown promise. Zhou et al. [13] constructed a water quality safety assessment system for reclaimed water reuse projects using the fuzzy comprehensive evaluation method. Wu et al. [14] improved the DRASTIC model to quantify the potential pollution risks associated with reclaimed water irrigation. Despite these advancements, these approaches remain constrained to specific contexts, and a general evaluation paradigm tailored to the characteristics of reclaimed water ecological replenishment has yet to emerge.

Moreover, evaluation methods from other disciplines have gained increasing application in water quality and ecological assessments.

The entropy weight method assigns weights based on the dispersion degree of indicators, effectively mitigating subjective bias and significantly enhancing the objectivity of water quality evaluations [15]. The analytic hierarchy process (AHP) systematically incorporates multi-dimensional parameters such as pollutant toxicity and ecological sensitivity by integrating subjective judgment with quantitative analysis [16,17]. The technique for order preference by similarity to ideal solution (TOPSIS) addresses multi-criteria trade-offs, offering intuitive support for complex water environment decision-making [18,19]. However, both the entropy weight method and AHP method have their respective shortcomings in weight determination. The entropy method overemphasizes the objectivity of data differences, while AHP depends on the subjective judgment of the evaluator regarding the importance of water quality and ecological indicators. TOPSIS is widely adopted for evaluating water resource carrying capacity. In prior studies, most researchers have utilized either the entropy method or AHP individually to calculate weights for environmental assessment [20,21], often resulting in evaluations that are overly reliant on either objective data fluctuations or subjective interpretations. To overcome the limitations of single-weighting methods, researchers have developed Entropy-AHP-TOPSIS model that integrates subjective and objective weighting approaches. While the method has been applied in fields such as evaluation of marine ranching [22] and selection of suitable plant species [23], its application to the multidimensional comprehensive impact assessment of reclaimed water on river water environment (including water quality and ecological indicators) with specific improvements remains an exploratory endeavor.

In this study, an improved Entropy-AHP-TOPSIS method (IEATM) is employed to evaluate the effects of reclaimed water from wastewater treatment plant on the water quality and ecological indicators in adjacent rivers. Furthermore, a systematic comparison is conducted between this method and traditional single-factor evaluation and comprehensive pollution index approaches, aiming to expand its applicability in environmental assessment contexts.

Materials and methods

Study area

The core study area was centered on a wastewater treatment plant (WWTP) located in Yinzhou district, Ningbo city. The surrounding rivers, including Heng River, Changfeng River, Dazhujia River, Qiantang River, and Xin River, collectively formed a typical demonstration zone for reclaimed water ecological supplement. The study period spanned one year, from January 2024 to December 2024, ensuring sufficient temporal coverage. The Changfeng WWTP is the largest one in Ningbo's central urban area, covering an area of approximately 22 hectares with a daily treatment capacity of 320,000 tons. It utilizes a combined process of moving bed biofilm reactor, high-density sedimentation tank, and cloth media filtration. The treated water meets stringent standards, with NH_3-N concentration at 0.031 mg/L, TP concentration at 0.108 mg/L, and permanganate index (PI) at 2.598 mg/L, all exceeding the provincial clean discharge standards. Employing technologies such as micro-nano bubble activation and constructed wetlands, the plant supplies 160,000 tons of reclaimed water per day to the surrounding rivers, significantly improving the regional water environment. In our study area, the river water replenishment is

40,000 tons per day.

To ensure the representativeness and scientific rigor of the monitoring data, five monitoring points were established, as shown in Fig.1. The following rivers and their respective monitoring points are designated for water quality analysis: the Heng River at Point 1, the Changfeng River at Point 2, the Dazhujia River at Point 3, the Qiantang River at Point 4, and the Xin River at Point 5. These points are strategically located to ensure comprehensive and accurate data collection across the various water bodies, and the distances between each adjacent point were approximately 500 meters. All points were located downstream of the Changfeng WWTP at varying distances to investigate water quality changes along the reclaimed water conveyance path. Taking into account river hydrology and the surrounding environment, Point 1 was positioned approximately 100 meters downstream of the replenishment discharge point. Subsequent monitoring points were placed sequentially along the river flow direction, each about 500 meters apart. This configuration aimed to effectively capture the processes of reclaimed water diffusion, mixing, and water quality evolution within the river channel, minimizing bias in monitoring results that could arise from excessive distance disparities, and ensuring data comparability and maintaining the systematic nature of the study. Moreover, the widths of several rivers, from upstream to downstream, are sequentially 11 m, 16 m, 12 m, 41 m, and 22 m. In the study area, the river flow velocity is 0 m/s under normal conditions, but during water supplement, it increases to approximately 0.04 m/s.

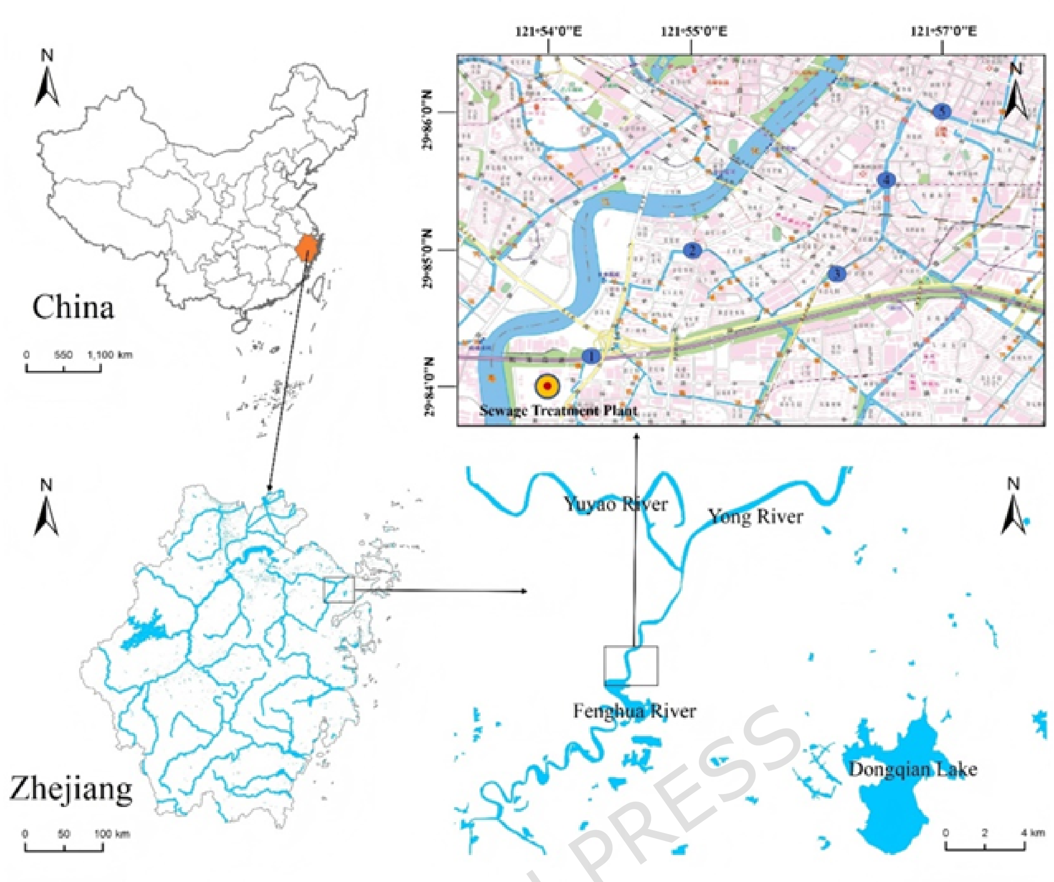

Figure 1. Spatial distribution of monitoring points along the reclaimed water replenishment river channels

Water sample collection and analysis

Data collection was conducted monthly from January to December 2024, encompassing field sampling and laboratory analysis. During the first ten days of each month, samples were collected at a depth of 0.5 meters beneath the water surface. At each sampling site, three replicate samples were gathered to ensure consistency and reliability. The sampling procedures complied with GB 3838-2002 and HJ 494-2009 ("Technical Guidelines for Water Quality Sampling"). The analytical methods employed adhered to the standardized protocols specified in the book of water and wastewater monitoring and analysis. To derive the baseline dataset for each parameter at each sampling site and time, the triplicate samples were averaged, maintaining a systematic and precise approach throughout the study. The monthly regenerated water reuse river water quality monitoring data can be found in Table S1.

Assessment methods construction

Traditional methods

The traditional single-factor method (TSFM) operates on a "one-strike" principle. According to this method, if any single water quality indicator exceeds its standard limit among all assessed parameters, the water body is deemed to fail in meeting its designated use function [24]. Water quality is quantified based on the most degraded indicator observed. The comprehensive pollution index method (CPIM) calculates the pollution index for each water quality parameter as the ratio of its measured value to its corresponding evaluation standard. These individual pollution indices are then averaged using equal weights to determine the comprehensive pollution index [25]. The process involves the following steps:

Step 1: Calculate the one-factor index. The equation is as follows:

$$Q=\max(Q_i) \tag{1}$$

Where Q represents the comprehensive water quality classification determined by the single factor method; Q_i represents the water quality classification based on parameter i; and $\max$ denotes the worst classification among all i indicators.

Step 2: Calculate the individual pollution index of the general index. The equation is as follows:

$$P_i=C_i/S_i \tag{2}$$

For intermediate indicators, the formulas are as follows:

$$P=0,\ C_i \geq C_s \tag{3}$$

$$P=\frac{C_s-C_i}{C_s-C_{min}},\ C_i < C_s \tag{4}$$

Where P_i represents the relative pollution value of the i^{th} factor; C_i represents the measured concentration value of the ith factor; S_i represents the standard value of the ith factor for Class III water areas; represents the middle-range standard value of the target water quality category; and C_{min} represents the minimum allowable value.

Step 3: Calculate the average composite pollution index using equation:

$$P=1/n\sum_{i=1}^{n} P_i \tag{5}$$

Where n is the number of pollutant indicators evaluated. The water quality classification based on P is as follows: $P \leq 0.20$ (Excellent); $0.21 < P \leq 0.40$ (Good); $0.41 < P \leq 0.70$ (Slightly polluted); $0.71 < P \leq 1.00$ (Moderately polluted); $1.01 < P \leq 2.00$ (Heavily polluted); $P > 2.00$ (Severely polluted).

Step 4: Calculate pollution contribution rate using the equation:

$$K_i=P_i/\sum_{i=1}^{n} P_i \times 100\% \tag{6}$$

Where K_i represents the pollution contribution rate of pollutant i at the monitoring section.

Improved Entropy-AHP-TOPSIS method

The IEATM was adopted for the comprehensive assessment of river water quality and ecological status. The entropy method determines indicator weights based on the information content reflected in the dispersion of the indicator data [26]. The AHP structures the decision problem into a hierarchy and utilizes pairwise comparisons based on expert judgment to assign weights that reflect the relative importance of each indicator [27]. The TOPSIS evaluates alternatives based on their proximity to the positive ideal solution and their separation from the negative ideal solution [28]. The specific steps are outlined in Fig.2.

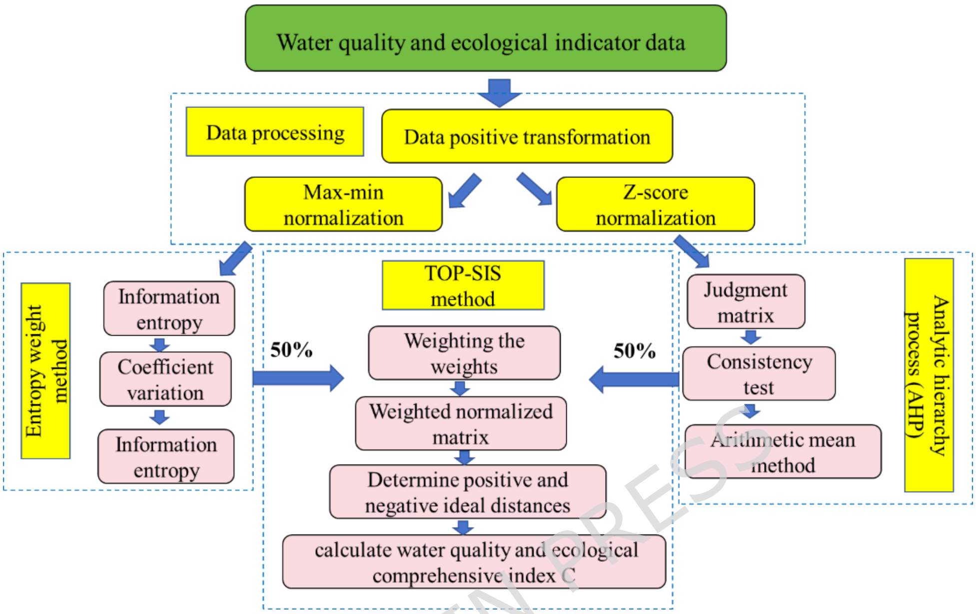

Figure 2. Evaluation steps of the improved Entropy-AHP-TOPSIS method

Step 1: Data forwardization. Standardization is conducted based on the directivity of the indicator. For negative indicators, the equation is as follows:

$$\bar{x} = max - x \tag{7}$$

Interval indicator processing:

$$M = max\{a - min\{x_i\}, max\{x_i\} - b\} \tag{8}$$

$$\tilde{x}_i = 1 - \frac{a - x_i}{M}, x_i < a \tag{9}$$

$$\tilde{x}_i = 1, a \leq x_i \leq b \tag{10}$$

$$\tilde{x}_i = 1 - \frac{x_i - b}{M}, x_i > b \tag{11}$$

where M is the maximum value, which is used to measure the degree of deviation between the data point and the boundary of the optimal interval. a and b denote the upper and lower bounds of the optimal interval, respectively, with the objective of ensuring that data points lie within [a,b]; $\min\{x_i\}$ is the minimum value in the original data. $\max\{x_i\}$ is the maximum value in the original data. x_i is the ith data point in the original data, which is a value in the interval series. $\tilde{x}_i$ is the value of the ith data point after forwardization.

Step 2: Data standardization for entropy method. The Min-Max normalization method is applied to data used for the Entropy Method. This method linearly transforms the original data to a specified [0,1] interval to eliminate the influence of different dimensions and units on evaluation results. the equation is as follows:

$$\tilde{x}_{ij}=\frac{x_{ij}-\min(x_j)}{\max(x_j)-\min(x_j)} \tag{12}$$

Where x_{ij} represents the value of the jth indicator at the ith monitoring point; and the normalized value represents the normalized value of $\tilde{x}_{ij}$, respectively.

Step 3: Z-score standardization for AHP. For data requiring weighting via the AHP method, the Z-score standardization method is used to transform data into standard normal distribution data with a mean of 0 and a standard deviation of 1, thereby eliminating dimensional differences between data. the equation is as follows:

$$z=\frac{X-u}{\sigma} \tag{13}$$

where X is the original data point; u is the mean value of the dataset; σ is the standard deviation of the dataset.

Step 4: Calculate information entropy. the equation is as follows:

$$e_j=-k\sum_{i=1}^{n} p_{ij}\ln p_{ij} \tag{14}$$

$$k=\frac{1}{\ln n} \tag{15}$$

Step 5: Calculate the coefficient of variation. the equation is as follows:

$$d_j = 1 - e_j \tag{16}$$

where d_j is the coefficient of difference.

Step 6: Determine Weights Based on Coefficient of Variation. the equation is as follows:

$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j} \tag{17}$$

Where w_j is the weight of each indicator.

Step 7: Construct judgment matrix for AHP. Based on the relative importance of each indicator, construct a pairwise comparison judgment matrix. The seven parameters considered are PI, NH_3-N, TP, DO, algal bloom index (ABI), Chlorophyll *a* (Chl *a*), and fecal coliforms (FC). Construction details of the judgment matrix can be found in Tables S2 and S3.

Step 8: Calculate the Consistency Index (CI) and find the corresponding Random Consistency Index (RI) from Table S4. Then compute the Consistency Ratio (CR) using the following equation:

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{18}$$

$$CR = \frac{CI}{RI} \tag{19}$$

The calculated CI is 0.0017, and the CR is 0.001, which is less than 0.1. This indicates that the constructed judgment matrix is reasonable and reliable.

Step 9: Calculate the weights using the Arithmetic Mean Method. the equation is as follows:

$$w_j = \frac{1}{n} \sum_{j=1}^{n} \frac{a_{ij}}{\sum_{k=1}^{n} a_{kj}} \tag{20}$$

Step 10: The weights obtained by the entropy method and AHP method are weighted according to 50% of the weights respectively to obtain Table S5.

The equation is as follows:

$$w_j=w_{j1}\times 50\%+w_{j2}\times 50\% \tag{21}$$

Step 11: Calculate the weighted standardized matrix:

$$v_{ij}=w_j\cdot x_{ij} \tag{22}$$

Where v_{ij} is the weighted normalized value; w_j is the weight of each indicator;x_{ij} is the normalized value of the indicator.

Step 12: Determine the positive ideal solution (PIS) and negative ideal solution(NIS). the equation is as follows:

$$A^{+}=(\max v_{ij})_{m\times 1} \tag{23}$$

$$A^{-}=(\min v_{ij})_{m\times 1} \tag{24}$$

Step 13: Compute the euclidean distance from each evaluation object to PIS and NIS. the equation is as follows:

$$S_i^{+}=\sqrt{\sum_{j=1}^{m}\left(v_{ji}-A_j^{+}\right)^2} \tag{25}$$

$$S_i^{-}=\sqrt{\sum_{j=1}^{m}(v_{ji}-A_j^{-})^2} \tag{26}$$

Step 14: Calculate the comprehensive Water-Ecological Index (C) for each evaluation object. the equation is as follows:

$$C_i=\frac{S_i^{-}}{S_i^{+}+S_i^{-}} \tag{27}$$

Where $C_i\in[0,1]$, higher C values indicate better water-ecological status. The classification is: $C>0.95$ (Excellent); $0.85<C\leq 0.95$ (Good); $0.75<C\leq 0.85$ (Slightly polluted); $0.65<C\leq 0.75$ (Moderately polluted); $0.55<C\leq 0.65$ (Heavily polluted); $C\leq 0.55$ (Severely polluted).

Results

Analysis of assessment results

To calibrate the method with measured data, the following optimizations were implemented. 1) Water quality indicators, including PI, NH_3-N, TP, and FC (a key riverine indicator [29]), were categorized as negative indicators (where higher concentrations correspond to poorer water quality) according to GB 3838-2002. It has been demonstrated by previous studies that reclaimed water generally exerts a stronger ecological impact on algae compared to bacteria [10], and that planktonic bacterial communities in watercourses consistently supplemented with reclaimed water show less pronounced seasonal variation [30]. Therefore, we have prioritized the analysis of algae by identifying DO, ABI, and chl *a* as critical interval-type indicators in the evaluation of aquatic environments and ecosystems. These indicators are characterized by an optimal ecological range (OER) rather than simply being strictly maximization or minimization type. Specifically, excessively low or high DO concentrations, along with elevated ABI and chl *a* concentrations, signal algal bloom risks. Based on recent studies [31,32], their optimal intervals were defined as DO: 5-7.5 mg/L, ABI: 0-0.2, chl *a*: 0-10 μg/L. Equations (8)-(11) were utilized to convert these interval-type indicator values into comparable, unified positive indicators within the evaluation system; 2) Indicator weighting was determined using a hybrid approach that combined both subjective and objective methods. Objective weights were calculated through the entropy method, which relies on data dispersion, while subjective weights were established using the AHP based on expert judgment matrices. This approach intentionally assigned higher weights to ecological indicators, such as ABI and chl *a*, to emphasize the critical role of algae in energy flow and nutrient cycling [31,32]. The combined weights were derived using a balanced 50:50 weighting scheme (Equation 21), ensuring that the assessment effectively integrates data objectivity with ecological logic; 3) Ecological stability was quantified using a dynamic closeness coefficient, calculated via the TOPSIS method. This comprehensive index measures the proximity of the evaluated object to an ideal ecological state.

Table 1 presents the assessment results of the TSFM, the CPIM, and the IEATM. The TSFM demonstrates significant advantages in determining water quality compliance. For instance, in January at Monitoring Point 3, the NH_3-N concentration significantly increased to 6.89 mg/L (Table S1), exceeding the "Class III" water quality standard by 5.89 times. The TSFM directly classified it as "Class V" water, reflecting the severe chemical pollution during that period. The CPIM further highlighted its sensitivity to high pollutant concentrations by quantifying the pollution level as P=2.627 ("Severely polluted"). Notably, Monitoring Point 3 exhibited a marked transformation in evaluation results before and after May, indicating that river pollution alleviated and water quality improved with the onset of the rainy season [33]. Both TSFM and CPIM were capable of better reflecting this change.

The IEATM enhances the effectiveness and accuracy of evaluations by assigning weights to water quality and ecological indicators. For instance, annual data from Monitoring Point 1 (Table S1) shows that while TP concentrations in September and October (0.23 mg/L) slightly exceeded the Class III standard (0.20 mg/L), all other indicators met the Class III criteria or remained within their optimal ranges. The calculated C values were consistently above 0.85 ("Good"), indicating that the short-term fluctuations in a single indicator did not compromise the overall integrity of the water body's ecological functions, thereby showcasing the method's strength in comprehensive evaluations. During May, June, and September at Monitoring Piont 2, the algal bloom index exceeded the optimal range by 0.7 times. The IEATM classifies the condition as "Slightly polluted" water. In comparison, the traditional evaluation method categorizes these as "Class V" water and "Severely polluted" water, respectively. The classification of IEATM is more reasonable, as it takes into account the self-purification capability of the water environment. Similarly, data from Monitoring Point 3 in January revealed that DO concentrations (1.19 mg/L) fell below the optimal range (5-7.5 mg/L), and the ABI (0.62) also exceeded its optimal range, signaling simultaneous deteriorations in chemical pollution and ecological degradation. The IEATM yielded a C value of 0.396 ("Severely polluted"), better reflecting the water body's chemical contamination while also highlighting the ecological risk of its self-purification capacity being nearly lost. Looking at the annual data for Monitoring Point 2, although FC concentrations severely exceeded standards in specific months (with the highest excess reaching 34 times the threshold), other water quality and ecological indicators performed well. The IEATM calculated an annual mean C Value of 0.902 ("Good"), suggesting that the water body's self-purification capacity had not been significantly impaired and that ecological stability was still intact [34].

Table 1. Evaluation results obtained by three evaluation models

River	Point	Month	TSFM	CPIM		IEATM	
				P	Contamination situation	C	Contamination situation
Heng River	1	4	IV	0.27	Good	0.9663	Excellent
		7	IV	0.342	Good	0.9528	Excellent
		8	IV	0.349	Good	0.9509	Excellent
		11	IV	0.222	Good	0.950	Excellent

						3	
		12	IV	0.286	Good	0.9642	Excellent
Changfeng River	2	1	V	5.239	Severely polluted	0.8749	Good
		2	V	1.139	Heavily polluted	0.9382	Good
		3	V	1.958	Heavily polluted	0.8668	Good
		4	V	1.033	Heavily polluted	0.9522	Excellent
		5	V	5.248	Severely polluted	0.7836	Slightly polluted
		6	V	7.465	Severely polluted	0.7533	Slightly polluted
		7	V	4.878	Severely polluted	0.8799	Good
		8	V	7.383	Severely polluted	0.8492	Slightly polluted
		9	V	3.103	Severely polluted	0.7872	Slightly polluted
		10	V	3.178	Severely polluted	0.896	Good
		11	V	1.956	Heavily polluted	0.9102	Good
		12	IV	1.615	Heavily polluted	0.9664	Excellent
Dazhujia River	3	1	V	2.627	Severely polluted	0.3958	Severely polluted
		5	IV	0.97	Moderately polluted	0.8439	Slightly polluted
		7	IV	4.878	Heavily polluted	0.6884	Moderately polluted
		8	V	7.383	Heavily polluted	0.8483	Slightly polluted
		9	IV	3.103	Moderately polluted	0.637	Heavily polluted
		10	V	3.178	Severely polluted	0.8391	Slightly polluted
		11	V	1.956	Severely polluted	0.917	Good
		12	V	1.615	Moderately polluted	0.9031	Good

Qiantang River	4	3	IV	1.303	Heavily polluted	0.8428	Slightly polluted
		4	V	4.06	Severely polluted	0.7047	Moderately polluted
		10	V	11.863	Severely polluted	0.6921	Moderately polluted
		11	V	3.306	Severely polluted	0.8335	Slightly polluted
		12	V	11.993	Severely polluted	0.6544	Moderately polluted
Xin River	5	3	V	1.413	Heavily polluted	0.6116	Moderately polluted
		4	V	1.898	Heavily polluted	0.6884	Moderately polluted
		5	IV	1.032	Heavily polluted	0.6427	Moderately polluted
		11	V	7.768	Severely polluted	0.7977	Slightly polluted
		12	V	4.605	Severely polluted	0.6174	Moderately polluted

Comparison of assessment method results

Table 2 presents a comparison of the water quality standard values, measured values, and weight allocations for Monitoring Point 3 in January. The CPIM fails to assign weights to ecological indicators, which limits its ability to reflect changes in water body ecological functions. For example, in January at Monitoring Point 3, while both methods classify the water quality as "Severely polluted," their underlying criteria differ. The CPIM attributes the pollution primarily to extreme NH_3-N levels (6.69 mg/L), with a pollution contribution rate of 53%, and a P value of 2.627 (Table 1). However, it fails to adequately capture the combined effects of low DO concentrations (1.19 mg/L, below the optimal range) and deteriorating algal indicators, which collectively indicate a collapse in the water body's self-purification capacity. In contrast, the IEATM employs a subjective-objective integrated weight allocation strategy, assigning higher weights to core ecological indicators, such as ABI (0.23) and chl *a* (0.17 ug/L). These weights reflect the central role of algae in aquatic ecosystems, particularly in energy flow and nutrient cycling [31]. By applying a combined weighting approach with a 50% proportion (Equation 21), the IEATM ensures a balance between data objectivity and ecological logic, thereby enhancing the scientific rigor and reliability of the assessment. The IEATM also better aligns with the integrity of water quality and ecological functions, capturing the deterioration of DO (1.19 mg/L), ABI (0.62), and chl *a* (27 ug/L), resulting in a calculated C value of 0.396 ("Severely polluted"). This value is 40% lower than the annual mean C value (0.699), providing a more holistic and precise reflection of the water body's severe chemical pollution and the collapse of its purification capacity, while also emphasizing the urgency of ecological function restoration.

Table 2. Comparison of standard values, measured values (January), and weight allocation for water quality and ecological indicators at Monitoring Point 3

Water quality indicators	Standard value	Measured value	Pollution contribution rate by traditional method	Weight by IEATM
PI	6 mg/L	4.99 mg/L	0.06	0.1285
NH_3-N	1 mg/L	6.89 mg/L	0.53	0.1316
TP	0.2 mg/L	0.77 mg/L	0.29	0.103
DO	5~7.5 mg/L	1.19 mg/L	0.06	0.1254
ABI	0~0.2	0.62	0	0.1823

Chl *a*	0~10 ug/L	27 ug/L	0	0.2138
FC	1×10^4 MPN/L	0.8×10^4 MPN/L	0.06	0.1155

As shown in Fig. 3a and 3b, the CPIM reveals that FC play a dominant role in water quality pollution across all months at Monitoring Point 2, with significant annual fluctuations. This is mainly due to the fact that Monitoring Point 2 is located within a residential area, making it highly susceptible to human activities. For instance, wastewater containing animal feces, soil bacteria, and household waste, especially during rain events, can easily enter the waterway, rapidly increasing FC levels in the short term [35]. FC exhibited the most severe exceedances throughout the year at Monitoring Point 2, reaching 34 times the standard limit in August and a minimum of 2.3 times in February. In contrast, other water quality indicators, such as TP, showed only 0.4 times exceedance in July, and the rest of the indicators remained within Class IV water standards (Table 3). The phenomenon is closely associated with the CPIM calculation process, where each pollution index is equally weighted to derive the CPIM. If a particular indicator is highly influenced by environmental factors, this approach can lead to an exaggerated deviation between the evaluation results and the actual conditions. While this method clearly captures the exceedances of specific pollutants and their instantaneous pollution levels, its limitation lies in its inability to fully account for the interactions between water quality indicators and ecological indicators, as well as their cumulative effects on the overall health of the water body. Consequently, it is inadequate for evaluating long-term and comprehensive impacts, such as those caused by reclaimed water replenishment on river ecosystems.

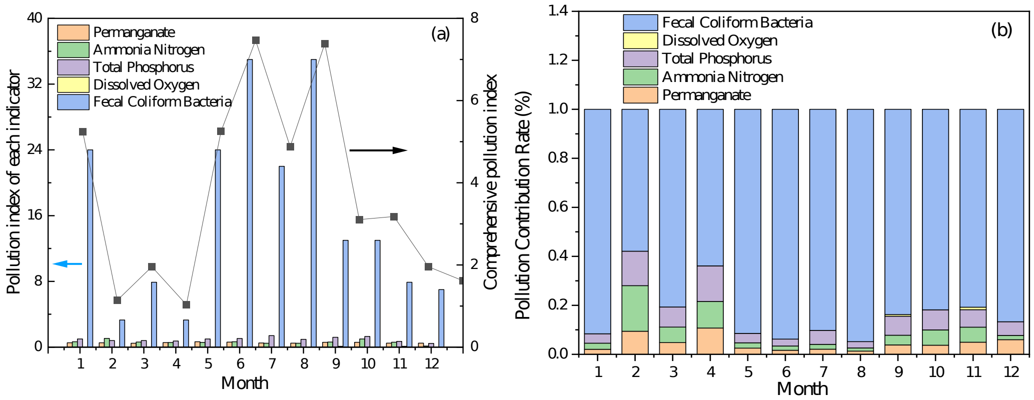

Figure 3. a) Temporal analysis of traditional comprehensive pollution index method evaluation results for Monitoring Point 2; and b) Monthly contribution rates of pollution indicators at Monitoring Point 2

The IEATM integrates water quality indicators with ecological indicators, constructing a multi-dimensional evaluation system for long-term environmental conditions. As shown in Table 3, lower weights are assigned to water quality indicators that are more susceptible to short-term environmental influences, such as FC and TP. This is because FC levels can rise sharply due to factors like rain-induced runoff carrying animal waste, soil bacteria, and urban pollutants into the river, while TP, despite exceeding standards (with a maximum multiplier of 0.4), does not indicate severe overall water quality degradation since other indicators comply with Class IV water standards. In the context of studying the impact of reclaimed water on river ecosystems, algae play a crucial role in energy flow and nutrient cycling within these systems [36,37]. High levels of pollutants in reclaimed water, such as organic matter, nitrogen, and phosphorus, can increase algal biomass [4], potentially leading to excessive algal proliferation and associated health risks from algal toxins by stimulating the growth of specific bloom-forming and toxin-producing species [33,38]. Additionally, algae serve as key primary producers and sensitive indicators in aquatic environments. Therefore, the IEATM assigns higher weights to ecological indicators like the ABI and chl *a* (which reflects algal abundance) [39,40], enabling a more comprehensive and long-term understanding of the river's overall condition. The method's output is a comprehensive index (C), which effectively reflects the long-term integrity of water quality and ecological functions. As demonstrated in Table 3, at Monitoring Point 2 throughout the year, although FC exceeded standards significantly, other water quality indicators were satisfactory, and most ecological indicators fell within optimal ranges. This suggests that the river's water quality remains good in the long term and exhibits strong ecological restoration capabilities [41]. Consequently, the annual mean value of the comprehensive index C (0.872), categorized as "Good" provides a more accurate and holistic representation of the river's situation when supplemented with reclaimed water, compared to traditional methods.

Table 3. Water quality and ecological indicators standards and measurements at monitoring point 2

	Factor	PI mg/L	NH_3-N mg/L	TP mg/L	DO mg/L	ABI	Chl *a* μg/L	FC $\times10^4$ MPN/L
	Standard Value	6	1	0.2	5~7.5	0~0.2	0~10	1
Point 2	Jan.	3.22	0.66	0.2	8.18	0.21	4	24
	Feb.	3.22	1.06	0.16	6.57	0.16	3	3.3
	Mar.	2.82	0.62	0.16	7.15	0.29	2	7.9
	Apr.	3.33	0.56	0.15	6.03	0.1	3	3.3
	May.	3.96	0.58	0.2	6.41	0.33	3	24
	Jun.	3.69	0.66	0.21	7.22	0.34	13	35
	Jul.	3.06	0.48	0.28	5.6	0.2	5	22

Aug.	2.9	0.48	0.19	5.95	0.2	5	35
Sep.	3.56	0.62	0.24	4.48	0.34	5	13
Oct.	3.53	1	0.26	6.01	0.09	2	13
Nov.	2.9	0.6	0.14	4.51	0.25	4	7.9
Dec.	2.9	0.14	0.09	6.19	0.02	2	7

Application of the IEATM in assessing the impact of reclaimed water on rivers

The application of the IEATM across five monitoring points revealed a distinct spatial gradient variation in the C values, as shown in Fig. 4a. The C values for Monitoring Points 1 to 5 were 0.935, 0.872, 0.699, 0.611, and 0.583, respectively, exhibiting a decreasing trend. Monitoring Point 1, located nearest to the reclaimed water source, maintained a consistently "Good" C value throughout the year. Its DO concentration remained stable, with a peak of 10.15 mg/L in January, and both ABI (≤0.18) and Chl *a* (≤3 μg/L) indicators consistently fell within the optimal ecological range.

At Monitoring Point 2, the CPIM yielded unfavorable results, while the IEATM provided a significantly better water quality evaluation. This discrepancy validated the phenomenon that water quality gradually deteriorates as the distance from the source increases during the conveyance of reclaimed water, a conclusion that aligns more closely with actual conditions. As the monitoring points progressed downstream, the C values continued to decrease. For example, the annual mean C Value at Monitoring Point 3 was 0.699, representing a reduction of approximately 25.24% compared to Monitoring Point 1. Additionally, the NH_3-N concentration at Monitoring Point 3 increased by 2.1 to 4.8 times that of Monitoring Point 1. This trend highlights the adverse effects of nutrient accumulation on the aquatic ecosystem, particularly under summer high-temperature conditions [42], where the algal bloom index significantly worsened, indicating an escalated risk of eutrophication [43]. At Monitoring Point 5, the C value further declined to 0.583 ("Severely polluted"), and both nutrient concentrations and algal indicators deteriorated simultaneously. This suggests that the river segment at Monitoring Point 5 has been impacted by the cumulative effects of multiple pollutants, rendering the ecological benefits of reclaimed water nearly ineffective [44,45].

From a temporal analysis perspective, Fig. 4b reveals that C values exhibit marked seasonal fluctuations. On a yearly scale, monitoring points closer to the reclaimed water intake (Points 1 and 2) show relatively smaller fluctuations in C values, whereas points farther from the intake (Points 3-5) experience more pronounced variations. Analysis in conjunction with Table S1 indicates that during winter (January-March), low temperatures suppress microbial activity and algal growth, resulting in higher DO levels across monitoring points (e.g., DO at Point 1 in January reached 10.15 mg/L). Additionally, NH_3-N and TP concentrations remain relatively stable (e.g., the average NH_3-N concentration at Point 1 was 0.19 mg/L). However, low flow velocities in certain areas lead to the presence of FC (e.g., Point 2 recorded a maximum of 24×10^4 MPN/L during winter); In spring (April-June), rising water temperatures significantly enhance algal proliferation, as evidenced by elevated ABI and Chl *a* concentrations at Point 2 (e.g., chl *a* reached 13 μg/L in June). Furthermore, nitrogen and phosphorus inputs from reclaimed water replenishment may exacerbate downstream eutrophication risks (e.g., TP at Point 5 peaked at 0.51 mg/L); During summer (July-September), high temperatures further stimulate microbial activity and algal growth [46], leading to substantial DO consumption (e.g., DO at Point 3 dropped to 4.41 mg/L in September). Additionally, intense stormwater runoff causes fluctuations in pollutant concentrations (e.g., the PI at Point 4 surged to 9.27 mg/L in August), with some areas even experiencing algal blooms (e.g., Chl *a* at Point 4 reached 151 μg/L). Notably, despite these challenges, the replenishment of reclaimed water maintained relatively stable C values at Points 1 and 2 near the intake, while other distant points exhibited larger fluctuations; In autumn (October-December), enhanced river water mobility results in a partial recovery of DO concentrations (e.g., DO at Point 1 in November was 8.39 mg/L). However, the input of salts from reclaimed water replenishment (e.g., ions like Na^{+} and Ca^{2+}) may disrupt water ion balance, contributing to a decline in benthic community diversity (e.g., Chl *a* at Point 5 remained high at 33 μg/L in December). Additionally, Fig. 4b shows a lower C value at Point 3 during winter, which may be linked to winter flow disturbances causing the suspension and release of nutrients (e.g., TP at Point 3 reached 0.77 mg/L in January, significantly higher than other months). Furthermore, the river temperature in Ningbo during winter was approximately 12°C, providing favorable conditions for cold-tolerant algae to thrive under ample light, potentially consuming DO (e.g., DO at Point 5 dropped to 2.29 mg/L in January), thereby intensifying ecological risks [47,48].

The relatively low C value observed at Point 4 during summer may be attributed to increased influent loads, potentially leading to incomplete wastewater treatment and elevated pollutant concentrations, which could cause a decline in C values. Overall, the seasonal variations in water quality and ecological indices in the river are effectively identified by the IEATM. Through analysis of C values and raw measurement data, it is evident that these seasonal fluctuations are primarily driven by hydrological conditions and temperature changes.

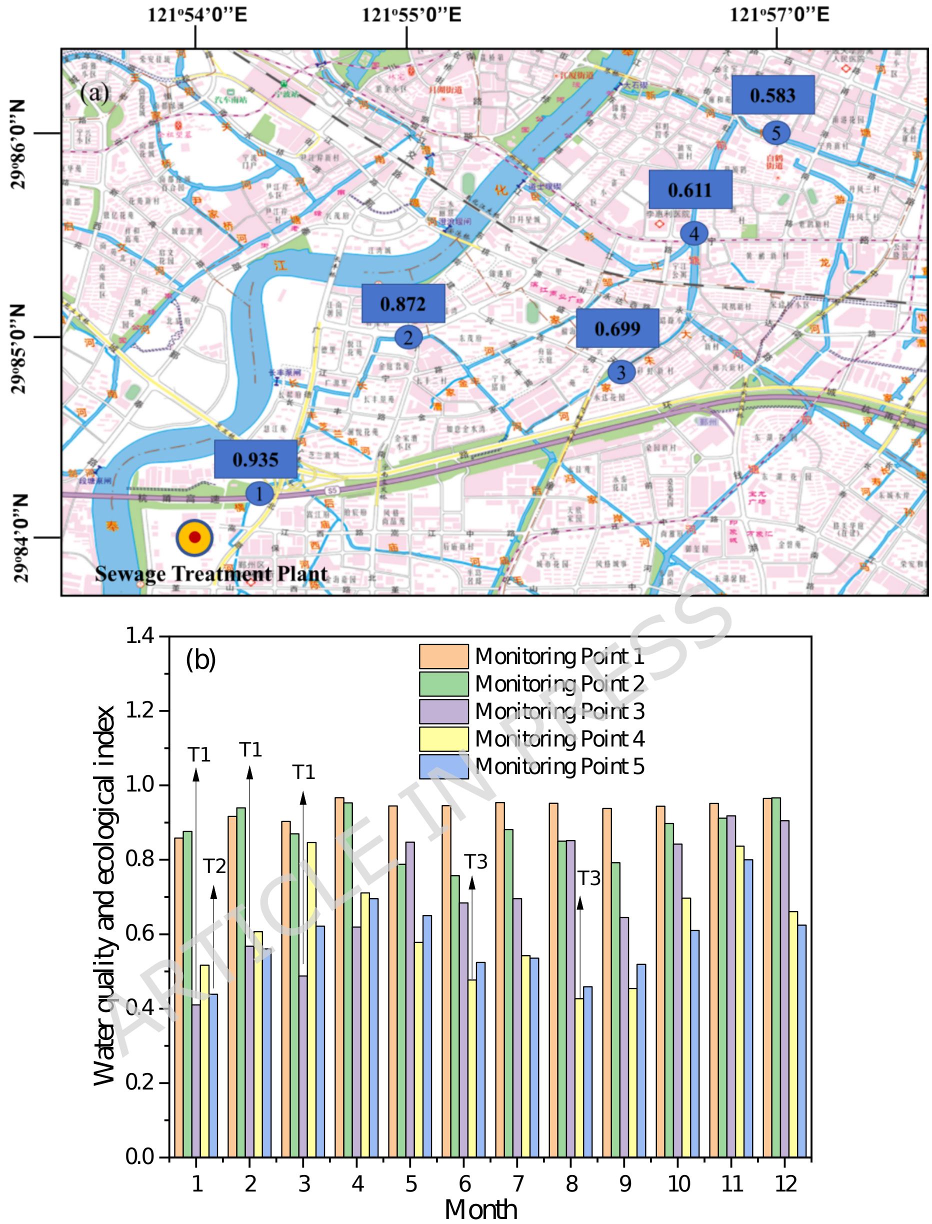

Figure 4. The water quality-ecological comprehensive index (C) at five monitoring points, showing variations in a) spatial distribution; and b) temporal trends. Note: T1 - sediment disturbance; T2 - cold-preferring algae; and T3 - rainwater flushing.

Discussion

Limitations of traditional assessment methods and related improvements

TSFM and CPIM both exhibit its limitations when assessing water quality in our study. TSFM employs a "one-vote veto" logic, focusing solely on the concentration thresholds of water quality indicators while neglecting the impact of ecological indicators on the overall health of water bodies. For instance, in January data from Monitoring Point 3, the traditional method classified the water as "Class V" due to excessive NH_3-N concentrations, yet it failed to reflect the low DO levels (1.19 mg/L) below the optimal range and the collapse of the water body's self-purification capacity caused by deteriorating algal indicators [30]. The CPIM (P value) can quantify pollution levels, but it has limitations in assessing the long-term ecological effects of reclaimed water replenishment in rivers. For example, at Monitoring Point 2, the annual FC concentration exceeded standards significantly, yet other water quality and ecological indicators remained favorable. In this case, the traditional "Severely polluted" classification might underestimate the water body's self-purification capacity [33]. This limitation highlights the "overgeneralization" issue inherent in traditional methods when assessing long-term ecological impacts, making it difficult to comprehensively reflect the integrated health status of water bodies.

In recent years, many researchers have made improvements to the comprehensive pollution index method in water quality evaluations. For example, integrating geographic information systems (GIS) with machine learning models, Das [49] have utilized the inverse distance weighting (IDW) interpolation technique in GIS to generate predictive maps of water quality parameters. Simultaneously, machine learning models have been employed to optimize calculation methods. Additionally, improvements have been made in the selection of input parameters by screening key parameters and reducing reliance on multiple parameters, thereby enhancing the method's generalizability and practicality [50].

Furthermore, Arzhangi et al. [51] have incorporated multiple water quality influence factors by integrating oxygen-related indicators (e.g., DO and oxygen deficit) with other critical water quality parameters to develop a more comprehensive evaluation framework.

Strengths and limitations of the IEATM

The IEATM integrates the weighting mechanisms of Entropy and AHP with the multi-criteria evaluation model of TOPSIS, significantly enhancing the scientific rigor and comprehensiveness of assessment results. The Entropy method assigns weights based on the dispersion of indicator data, providing an objective foundation for weighting. The AHP method constructs a hierarchical evaluation system and uses expert judgment matrices to assign higher weights to ecological indicators, such as algal-related indices, reflecting the critical role of algae in aquatic ecosystems [31]. The combined weights are assigned using a 50% weighting ratio, ensuring a balanced consideration of data objectivity and ecological logic in the evaluation process. It is worth noting that ecological indicators not only serve as sensitive indicators for water pollution but also play a crucial role in reflecting the water body's self-purification capacity and ecological restoration ability [40]. The IEATM integrates ecological indicators, such as the ABI and chl *a*, as core evaluation criteria, which significantly enhances the assessment of water ecological health. Furthermore, by analyzing the output of C values in conjunction with raw monitoring data, this approach provides an in-depth understanding of the specific causes behind abnormal C values, thereby offering scientific evidence for the regulation and control of ecological risk sources.

Despite its advantages, the IEATM also has limitations. Firstly, the output C value quantifies a specific river segment but lacks transitional judgments between intervals. Future improvements could incorporate fuzzy logic reasoning to address boundary issues, thereby facilitating dynamic perspectives in analysis. Secondly, the weighting ratios of different parameters significantly influence the C value output. For example, increasing the weight of FC or reducing the weights of indicators like chl *a* can alter the C value results. Thus, assigning appropriate weights to indicator parameters is particularly important, as it requires comprehensive consideration of various decision-making factors, including socio-economic aspects and environmental safety concerns [52]. Lastly, the method's applicability may be constrained by the characteristics of river ecosystems and variations in water replenishment strategies. Further validation and adaptability analyses in diverse scenarios are needed to expand its application scope and refine its practicality.

Potential management implications

The replenishment of reclaimed water to rivers currently faces challenges such as effect attenuation, nutrient accumulation, and an incomplete monitoring system. To address these issues, we propose the following solutions:

Firstly, leveraging the spatial variation characteristics of the C value, we recommend establishing a network of strategic replenishment points along the main river and its tributaries. This multi-point replenishment strategy enables segmented, controlled dilution of pollutants, thereby enhancing water circulation and DO levels [53]. Such a system would effectively mitigate the reduced self-purification capacity observed in downstream areas.

Secondly, in close proximity to the points where reclaimed water is introduced into the river, we recommend establishing constructed ecological buffer zones, such as wetlands and floating islands. These zones harness the adsorption and degradation capabilities of aquatic plants and microorganisms to minimize the immediate impact of reclaimed water on river ecosystems and mitigate the risk of eutrophication [54]. Additionally, the periodic removal of sediments and pollutants from the riverbed should be prioritized to reduce internal pollution sources and further improve water quality.

Lastly, the current monitoring framework heavily relies on conventional water quality parameters, with a lack of emphasis on ecological indicators. To mitigate this issue, comprehensive assessment methods, such as the Entropy-AHP-TOPSIS method, should be integrated into the monitoring framework. During the summer season, there should be a prioritization of monitoring and controlling algal growth, employing measures such as biological manipulation and chemical algae control. In winter months, attention should shift to sediment disturbance and the influence of cold-resistant algae species, which necessitates the implementation of optimized ecological dispatch plans to mitigate pollution risks. Moreover, a real-time monitoring system should be implemented to continuously track changes in both reclaimed water and river water quality, enabling timely identification and resolution of potential issues. Based on the C-values, the replenishment plan should be adjusted accordingly to ensure the continuous improvement of water quality enhancement measures.

Conclusion

The improved Entropy-AHP-TOPSIS method developed in this study integrates water quality and ecological indicators, achieving a balance between discrepancies in objective data and expert experience. This method provides a comprehensive and precise assessment of the impact of reclaimed water on river water environments. Compared to traditional methods, IEATM exhibits more noticeable advantages in terms of its comprehensiveness, objectivity, and precision. Importantly, it mitigates the undue influence of short-term fluctuations in individual indicators on overall evaluation results, thereby providing a more reliable assessment of the ecological effects associated with reclaimed water. The research findings reveal that the impact of reclaimed water replenishment on river water quality and ecology is complex. Near the replenishment region, the method shows that water quality improvement is notably effective. However, in the mid- and downstream sections, there is a potential risk of eutrophication due to nutrient accumulation. Additionally, the ecological impacts of reclaimed water replenishment exhibit distinct spatial attenuation characteristics and seasonal variation patterns. These findings not only provide a scientific basis for optimizing the replenishment strategy of reclaimed water but also contribute theoretical support for enhancing the ecological health of river systems. Furthermore, the results underscore the importance of considering spatial and temporal factors in evaluating the ecological effects of reclaimed water. Future studies should focus on validating and analyzing the adaptability of IEATM across diverse scenarios to refine its application and broaden its scope.

Declaration of interests：

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:

The data are available upon request and with the permission of Ningbo Municipal River Management Center.

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Authorship contribution:

Yongxing Qian: Writing – original draft, Software, Methodology, Investigation; Jingran Zhou: Writing – original draft, Software, Data curation, Methodology; Jinxi Chen: Writing – original draft, Software, Methodology, Investigation; Jiwei Chen: Data curation, Methodology; Zhiwu Liu: Writing –Writing – review & editing, Software; HuixiaJin: Writing – review & editing, Software, Funding acquisition, Conceptualization. All authors reviewed the manuscript.

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