INSS Press

Journal of Intelligent and Sustainable Systems

Article

Enhanced Objectivity and Efficiency in Sediment Ecological Risk Assessment: An Improved AHP Approach

Huaqing Zhang [1], Lei Li [2*], Hui Qiu[3], Junhao Chen[4], Wenran Chen[5]

[1] School of Earth Sciences and Engineering, Hohai University, Nanjing 211100, China; 250409030005@hhu.edu.cn
[2] School of Earth Sciences and Engineering, Hohai University, Nanjing 211100, China; lilei@hhu.edu.cn
[3] PowerChina Huadong Engineering Co., Hangzhou, Zhejiang, 311122, China; qiu_h@hdec.com
[4] PowerChina Huadong Engineering Co., Hangzhou, Zhejiang, 311122, China; chen_jh4@hdec.com
[5] Yangtze Ecology and Environment Co., Wuhan, Hubei, 430014, China; chen_wenran@ctg.com.cn

[*] Correspondence: School of Earth Sciences and Engineering, Hohai University, Nanjing 211100, China; lilei@hhu.edu.cn

Abstract

Scientifically managing sediment dredging in rivers and lakes is essential for sustaining aquatic ecosystems, and ecological risk assessment provides a key tool for balancing dredging benefits against potential ecological impacts. To overcome the limitations of the traditional Analytic Hierarchy Process (AHP)—namely, subjective adjustments and inefficiency in consistency testing—this study employs an improved AHP based on an optimal transfer matrix. This method constructs consistent judgment matrices, enhancing the objectivity and stability of weight determination. The approach is applied to sediments from the coal mining subsidence areas of the Zhuxianzhuang and Luling Mines in Suzhou City, Anhui Province. Nutrient levels, organic matter content, and heavy metal concentrations were analyzed to classify ecological risks into three categories: mild, moderate, and severe. Results show that the Zhuxianzhuang mining area has a comprehensive risk score of 3.90 (mild pollution), with total phosphorus (467 mg/kg), nickel (32 mg/kg), and cadmium (0.6667 mg/kg) at moderate levels, while total nitrogen (817 mg/kg) and mercury (0.1285 mg/kg) pose relatively higher risks. The Luling mining area scores 3.98 (mild pollution), with low phosphorus and organic matter content but relatively elevated mercury levels (0.112 mg/kg). By applying the improved AHP to sediment risk assessment, this study demonstrates its effectiveness in avoiding manual adjustments and maintaining logical consistency, offering a more reliable and efficient analytical tool for quantifying risks and informing dredging decisions.

Keywords: River and Lake Sediments; Sediment Dredging Projects; Ecological Risk Assessment; Improved Analytic Hierarchy Process; Assessment Framework

1. Introduction

River and lake sediment dredging serves as a crucial measure for improving water eutrophication, managing black and odorous waterways, and alleviating reservoir siltation (Yan & Li, 2023). In recent years, with increasingly stringent environmental protection requirements, sediment management has become a research focus in the fields of water resources, environment, and ecology. Scientific dredging decisions not only affect engineering effectiveness but also directly influence the long-term health and sustainable development of aquatic ecosystems (Manap & Voulvoulis, 2015). Pollutants accumulated in sediments, such as nutrients, organic matter, and heavy metals, not only pose direct threats to water quality but may also transfer through the food chain, exerting profound impacts on aquatic organisms and the entire ecosystem (Wang et al., 2019; Yin, 2023). Therefore, establishing a scientific and comprehensive ecological risk assessment system holds significant guiding importance for balancing the ecological benefits and potential risks of dredging projects (Hseu, 2020).

Currently, ecological risk assessment for sediment dredging primarily focuses on single-pollutant risk evaluations, such as nitrogen, phosphorus, organic matter, and heavy metals (Li et al., 2015; Wu et al., 2019; Zhang et al., 2023). However, in practice, river and lake sediments often represent composite pollution types involving multiple contaminants (Yang et al., 2021; Yuan et al., 2021). Single-index evaluations are insufficient to comprehensively reflect the integrated ecological risks or fully reveal synergistic or antagonistic interactions among pollutants. Consequently, developing integrated assessment methods capable of incorporating multiple pollutants and quantifying their interactive effects has become a key issue requiring urgent resolution in this field.

The Analytic Hierarchy Process (AHP) is widely used in environmental risk assessment due to its effectiveness in handling multi-criteria decision-making problems. However, in practical applications, the consistency test in traditional AHP exhibits notable limitations (Ishizaka & Labib, 2009; Kong & Liu, 2005). As the number of evaluation indicators n increases, the number of pairwise comparisons grows rapidly at a rate of n(n-1)/2 (Bose, 2020a). Given the inherent fuzziness of human cognition, experts are often unable to ensure complete logical consistency across all judgments when dealing with large-scale indicator systems, frequently resulting in the random consistency ratio (CR) of the judgment matrix exceeding 0.1 (Wang, 2015). To forcibly pass the consistency test, evaluators often need to repeatedly and artificially fine-tune the original scores. This process of adjusting data merely to achieve consistency not only significantly increases computational costs but also severely undermines the originality and objectivity of the evaluation results (Gastes & Gaul, 2012; Wu et al., 2026).

To address the consistency issues in the traditional AHP method, researchers have proposed various improvements and hybrid approaches. For instance, fuzzy logic has been incorporated into fuzzy AHP to handle uncertainty and imprecision in judgments, thereby enhancing consistency (Zyoud et al., 2025). Some studies have combined the entropy weight method with AHP to construct hybrid evaluation models, mitigating subjective bias through objective weight adjustments (Zhong et al., 2022). Additionally, some scholars have attempted to introduce particle swarm optimization (PSO) or genetic algorithms (GA) to optimize AHP, reducing inconsistencies in calculations (Bose, 2020b, 2022). Although these methods improve accuracy to some extent, they significantly increase model complexity and mostly still follow the process of constructing a matrix first and then optimizing it upon detecting inconsistency. Currently, in the field of comprehensive ecological risk assessment for environmental sediments, there remains a lack of a method that can directly generate a consistent matrix through mathematical mechanisms, features a simple computational process, and is suitable for rapid engineering decision-making.

In recent years, to overcome the shortcomings of traditional AHP, the Optimal Transfer Matrix (OTM) has been introduced to improve the construction of judgment matrices and the weight determination process (Li et al., 2025). Unlike fuzzy AHP or entropy-based correction methods, the unique feature of the optimal transfer matrix is its inherent consistency. Instead of iteratively adjusting an existing matrix, it employs mathematical transformations to directly map experts' initial rankings into a judgment matrix that satisfies consistency requirements, theoretically eliminating the risk of CR test failure (Kabenla et al., 2024; Wen et al., 2023). This not only simplifies the computational process but, more importantly, reduces secondary subjective intervention by experts during repeated matrix adjustments, ensuring the logical rigor of evaluation weights (Gursoy et al., 2013). It also better handles interactions among pollutants, providing more precise comprehensive assessment results.

Therefore, this study selects the water diversion project in the coal mining subsidence areas of Zhuxianzhuang Mine and Luling Mine in Suzhou City, Anhui Province, as a case study. An improved AHP method is employed to comprehensively assess the interrelationships and combined effects of different pollutants in the sediments of this region. This approach aims to offer a new pathway with greater logical rigor and operational efficiency for sediment ecological risk assessment and multi-objective dredging decision-making.

2. Research Area and Sample Analysis

2.1. *Study area*

The project area is situated in Yongqiao District, Suzhou City, Anhui Province, China, primarily involving the coal mining subsidence areas of the Zhuxianzhuang Mine and the Luling Mine (Figure 1). Yongqiao District, Suzhou City, is a significant coal-electricity industrial base with abundant mineral resources, predominantly coal. Years of large-scale coal mining have led to severe ground subsidence in the region, forming extensive subsidence areas, including those of the Zhuxianzhuang Mine and the Luling Mine. The water surface areas of the subsidence zones in the Zhuxianzhuang Mine and the Luling Mine are 9 km² and 25.7 km², respectively, serving as the primary work zones for the dredging project. The project aims to comprehensively address regional water resource shortages and ecological environment restoration through the renovation of water treatment plants, improvement of water conservancy facilities, and implementation of water storage and regulation projects. Among these measures, constructing purification ponds is a core initiative for improving water quality, the effectiveness of which heavily relies on scientifically sound sediment dredging strategies. Due to the long-term accumulation of pollutants such as nitrogen, phosphorus, organic matter, and heavy metals, the coal mining subsidence areas of the Zhuxianzhuang Mine and the Luling Mine in Suzhou City have posed a threat to regional ecological health.

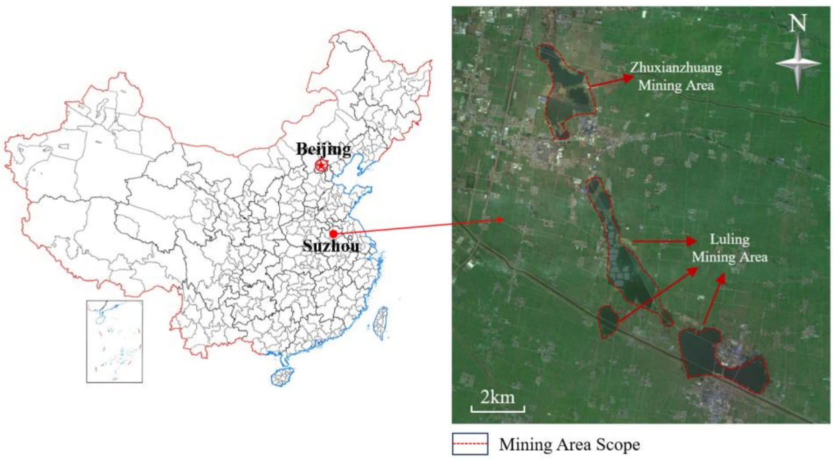

Figure 1: Location of the Study Area and Mining Area Boundary Map

2.2. *Sampling location and pollutant content characteristics*

This study designed the sampling points based on the physical characteristics of the coal mining subsidence area, such as weak hydrodynamics and relatively enclosed water bodies. Due to the stable sedimentary environment of such water bodies, the spatial distribution of the sediment exhibits significant homogeneity. This allows a limited number of samples to effectively reflect regional pollution levels. For this assessment, 6 and 11 sampling points were established in the Zhuxianzhuang and Luling mining areas, respectively (totaling 17 points). These points cover all planned central areas of the purification ponds and key pollutant discharge outlets along the waterways (specific locations are shown in Figure 2). This engineering-logic-based point layout ensures the samples' representativeness for evaluating dredging risks and the feasibility of purification pond construction.

The statistical characteristics of pollutants in the subsidence area sediments are presented in Table 1. Organic toxins were not detected and are therefore not considered in this study. The results show that the average concentrations of heavy metals Cu, Zn, Ni, Cr, Pb, Cd, Hg, and As were 21.24, 56.65, 31.59, 61.35, 15.89, 0.06, 0.12, and 4.86 mg/kg, respectively. The average contents of nitrogen, phosphorus, and organic matter were 700.71 mg/kg, 440.65 mg/kg, and 9.05 mg/kg, respectively. Regarding spatial distribution, except for Cd which had a lower concentration and slightly higher dispersion (coefficient of variation of 52%), the coefficients of variation for all other indicators fell within a relatively low range of 16% to 33%. This low level of variation objectively reflects the homogeneity of the sedimentary environment in the subsidence area, indicating a relatively stable spatial distribution of pollutants.

Assessing the ecological risk of sediments serves a dual purpose. On one hand, it enables a comprehensive evaluation of pollutants within the sediment, thereby quantifying pollutant concentrations and the degree of contamination. On the other hand, it predicts the potential hazards of pollutants to the ecosystem, particularly the ecological damage caused by the accumulation of heavy metal pollution, to prevent further exacerbation of contamination. A scientific and rational ecological risk assessment of sediments can optimize dredging strategies and resource allocation, enhancing project efficiency and effectiveness. This process is crucial for promoting the sustainable use of water sources, holding significant importance especially for ensuring continuous water supply and the rational allocation of water resources.

(a) Zhuxianzhuang Mining Area (b) Luling Mining Area

Figure. 2. Subsidence area sampling location map

Table 1 Descriptive Statistics of Pollutant Concentrations

Indicator	Mean (mg/kg)	Standard Deviation	Coefficient of Variation	Minimum (mg/kg)	Maximum (mg/kg)
Cu	21.24	3.70	0.17	15	28
Zn	56.65	9.69	0.17	42	76
Ni	31.59	5.18	0.16	21	40
Cr	61.35	12.12	0.20	46	101
Pb	15.89	4.51	0.28	9.1	23.6
Cd	0.06	0.03	0.52	0.01	0.12
Hg	0.12	0.03	0.29	0.056	0.165
As	4.86	1.58	0.33	2.04	8.28
TN	700.71	224.66	0.32	216	1400
TN	440.65	127.65	0.29	288	711
OM	9.05	2.79	0.31	3.3	20.5

3. Methods

3.1. *Evaluation Indicators and Evaluation System*

The risk of sediment nutrient pollution primarily stems from the potential hazards associated with excessive nutrients like nitrogen and phosphorus. Research shows that Total Nitrogen (TN) and Total Phosphorus (TP) in water bodies are the main factors influencing eutrophication (Ye et al., 2021). When excessive nitrogen, phosphorus, and other nutrients are released from the sediment, they cause water eutrophication, leading to the deterioration of the aquatic environment and thus damaging the river and lake ecosystem. Furthermore, besides nitrogen and phosphorus nutrients, Organic Matter (OM) is another important factor causing water body blackening, odour, and eutrophication (Yang et al., 2022). Some scholars have found a significant positive correlation between OM content and both TN and TP in river sediments (Dai et al., 2023). Therefore, this study selects TN, TP, and OM as evaluation indicators to assess the ecological risk level of nutrient pollutants in river and lake sediments.

Heavy metals feature accumulation and migration in the environment, capable of entering organisms through multiple pathways such as water, solid media, and air. They cause varying degrees of harm to plants and animals after magnification via the food chain (Yang et al., 2023). Due to the significant toxicity posed by heavy metals, numerous scholars both domestically and internationally have conducted extensive research, resulting in relatively mature risk assessment systems. Relevant literature has established contained limits for eight heavy metal elements: Lead (Pb), Cadmium (Cd), Zinc (Zn), Mercury (Hg), Chromium (Cr), Copper (Cu), Arsenic (As), and Nickel (Ni) (Herath et al., 2022; Xiang et al., 2021). Therefore, this paper selects eight heavy metals—Hg, Cd, As, Ni, Pb, Cu, Cr, and Zn—as evaluation indicators to assess the ecological risk level of heavy metal pollutants in river and lake sediments.

The evaluation system is divided into the goal layer, the criteria layer, and the indicator layer. The goal layer represents the final comprehensive evaluation result, namely the ecological risk assessment result of sediment in the river and lake sediment dredging project in the Zhuxianzhuang and Luling mining areas of the coal subsidence area in Guoqiao District, Suzhou City, Anhui Province. The criteria layer is divided into two levels: nutrient salt pollution and heavy metal pollution. Eleven detailed indicators are included in the indicator layer, as shown in Table 2.

Table 2: Sediment Ecological Risk Assessment Indicator System

Goal Layer	Criteria Layer	Indicator Number	Indicator Layer
Ecological Risk Assessment of Sediment	Nutrient Salts and Organic Matter(A)	A1	TN
		A2	TP
		A3	OM
	Heavy Metals(B)	B1	Mercury
		B2	Cadmium
		B3	Arsenic
		B4	Lead
		B5	Copper
		B6	Nickel
		B7	Chromium
		B8	Zinc

3.2. *Single Indicator Pollution Assessment Method*

The classification of pollutant concentration and pollution degree, derived from existing evaluation methods for single pollution types, was adopted as the scoring criteria. Each indicator was divided into five grades from lowest to highest (Karr et al., 1981). The best grade was assigned a score of 5, the worst grade a score of 1, and the middle grade a score of 3. The relatively better and relatively worse grades fall between the corresponding two and were assigned scores of 4 and 2, respectively. This scoring approach allows for a more intuitive reflection of the degree of sediment risk.

3.2.1. *Nutrient and organic pollution*

The Organic Index Method, the most commonly used approach, was adopted in this chapter to evaluate the extent of nutrient pollution in the sediments. The calculation formulas are as follows:

$$OI = OC(\%) \times ON(\%) \tag{1}$$

$$OC = \frac{OM(\%)}{1.724} \tag{2}$$

$$ON = TN(\%) \times 0.95 \tag{3}$$

Where: [OI] is the Organic Index; [OC] is the mass fraction of organic carbon substance (%); [ON] is the mass fraction of organic nitrogen substance (%).

Since the Organic Index Method lacks an evaluation of Total Phosphorus (TP) pollution levels, the Pollution Index Method is commonly used to assess the extent of phosphorus pollution in river sediments. The calculation formula is as follows:

$$P_i = \frac{C_i}{C_{ji}} \tag{4}$$

Where: [P_i] is the Pollution Index; [C_i] is the measured concentration of Total Phosphorus in the sediment, in mg/kg; and [C_{0i}] is the standard value corresponding to the environmental evaluation. The threshold used in this chapter that causes the lowest level of ecological risk effect is 600mg/kg (Wu et al., 2023).

According to the scoring rules of the assignment method (Li et al., 2024): when Pi⩽0.5, the river and lake sediment has no phosphorus pollution risk, representing the best grade; when 0.5＜Pi⩽1.0, the phosphorus pollution level is mild, representing the relatively good grade; when 1.0＜Pi⩽1.5, the phosphorus pollution level is moderate, representing the intermediate grade; and when Pi⩾1.5, the phosphorus pollution level is severe, representing the poor grade. The corresponding scores are shown in Table 3.

Table 3: Scores of the Pollution Index Method for Different Ranges

Grade	Pollution Index	Pollution Severity	Score
I	$P_i \leq 0.5$	No Pollution	5
II	$0.5 < P_i \leq 1.0$	Mild Pollution	4
III	$1.0 < P_i \leq 1.5$	Moderate Pollution	3
IV	$P_i \geq 1.5$	Severe Pollution	1

Similarly, the scoring values for the different degrees of organic matter pollution and Total Nitrogen pollution in the sediment, determined by the assignment method, are presented in Table 4.

Table 4: Scores of the Organic Index and Organic Nitrogen Index for Different Ranges

Grade	Organic Index	Organic Nitrogen Index	Pollution Severity	Score
I	<0.05	<0.033	No Pollution	5
II	0.05~0.2	0.033~0.066	Light Pollution	4
III	0.2~0.5	0.066~0.133	Moderate Pollution	3
IV	≥0.5	≥0.133	Severe Pollution	1

3.2.2. *Heavy metal pollution*

This chapter uses the Potential Ecological Risk Index method proposed by Hakanson as a reference (Şener et al., 2023) to assess the risk of heavy metal pollution. The calculation formula is:

$$C_f^i = \frac{C_s^i}{C_n^i} \tag{5}$$

Where: $[C_s^i]$ represents the measured value of heavy metal i; $[C_n^i]$ represents the environmental background value of heavy metal i; $[C_f^i]$ represents the pollution coefficient of heavy metal.
The pollution severity scoring based on different levels is shown in Table 5.

Table 5: Classification Standards and Scores for Potential Ecological Risks

Pollution Level	Pollution Coefficient	Risk Degree	Score
I	$C_f^i < 1$	Slight	5
II	$1 \leq C_f^i < 2$	Mild	4
III	$2 \leq C_f^i < 4$	Moderate	3
IV	$4 \leq C_f^i < 8$	Strong	2
V	$C_f^i \geq 8$	Severe	1

The comprehensive ecological risk level of river and lake sediment pollution is composed of the weighted scores corresponding to the pollution degree of all evaluation indicators in the indicator system. The calculation formula is:

$$S = \sum s_i \times w_i \tag{6}$$

Where: [S] is the comprehensive ecological risk score of the river and lake sediment; $[s_i]$ is the score corresponding to the pollution degree of the i-th indicator; $[w_i]$ is the weight of the i-th indicator.
This method can be used for ecological risk assessment of composite polluted sediments containing multiple types of pollutants. By quantifying the pollution degree of river and lake sediments, it visually reflects the ecological risk level of the sediments in numerical form. Additionally, it can provide sediment dredging recommendations based on related studies (Ferrans et al., 2021; Shou et al., 2022; Soetan et al., 2022; Weng, 2017). Table 6 lists the judgment criteria for this method.

Table 6: Overall Ecological Risk Level of Sediment

Assessment Score	Risk Level	Dredging Recommendations
3.5~5	Mild Pollution	The potential pollution risk of the sediment is relatively low. Shallowly contaminated sediment can be removed and utilised for resource recovery.
2~3.5	Moderate Pollution	Sediment contamination requires targeted removal of both shallow and deep sediments, with conditions suitable for resource recovery.
1~2	Severe Pollution	Sediment pollution is severe, making dredging highly necessary, and the environmental pollution risk associated with sediment disposal is high.

3.3. *Determination of Indicator Weights*

In sediment ecological risk assessment research, methods such as the fuzzy comprehensive evaluation method and the Analytic Hierarchy Process (AHP) exhibit certain limitations in determining indicator weights (Zhong et al., 2022b). This paper adopts the approach of improving the AHP using the Optimal Transfer Matrix, as referenced in current studies (Li et al., 2025; Ren et al., 2017; Ashour & Mahdiyar, 2024; Liu et al., 2020; Peláez & Lamata, 2003), to calculate the weights of indicators for sediment ecological risk assessment.

3.3.1. *Improving the Analytic Hierarchy Process*

In accordance with practical circumstances, after constructing the judgment matrix using the Analytic Hierarchy Process (AHP), the Optimal Transfer Matrix (OTM) is introduced to derive the OTM-based judgment matrix. The weights are then calculated according to the corresponding formula. This approach minimizes the interference of subjective factors with the evaluation results and eliminates the need for a consistency check. Mathematically, it ensures the logical self-consistency of the matrix, preserves the original judgment logic of the experts, and avoids the need for repeated adjustments to the raw data. This significantly reduces the computational burden and simplifies the weight calculation process for multi-indicator systems, making the computations more efficient (Xie & Xia, 2004).

3.3.2. *Optimal Transfer Matrix*

To achieve the aforementioned improvements, this study constructs the model based on the following mathematical logic. Let the real matrix be:

$$A=\left[a_{ij}\right],B=\left[b_{ij}\right],C=\left[c_{ij}\right]\in R_n\times n \tag{7}$$

Definition 1: If

$$a_{ij}=\frac{1}{a_{ij}} \tag{8}$$

then A is a reciprocal matrix; if

$$b_{ij}=-b_{ij} \tag{9}$$

then B is a skew-symmetric matrix.

Definition 2: If A is a reciprocal matrix and satisfies

$$a_{ij}=\frac{a_{ik}}{a_{jk}} \tag{10}$$

then A is consistent; if B is a skew-symmetric matrix and satisfies

$$b_{ij}=b_{ik}+b_{kj} \tag{11}$$

then B is transitive.

Definition 3: When the initial judgment does not satisfy transitivity, it is necessary to find a transitive matrix,

$$C = (c_{ij})_{n \times n} \tag{12}$$

such that its deviation from the original matrix is minimized, i.e.,

$$C = \min \sum_{i=1}^{n} \sum_{j=1}^{n} \left(a_{ij} - b_{ij} \right) \tag{13}$$

then C is referred to as the optimal transfer matrix of B.

Theorem 1: If B is a skew-symmetric matrix, then the optimal transfer matrix C of B should satisfy Equation 14.

$$c_{ij} = \frac{1}{n} \sum_{k=1}^{n} \left(a_{ik} - a_{jk} \right) \tag{14}$$

Theorem 2: If A is a reciprocal matrix,

$$B = \log A \tag{15}$$

and C is the optimal transfer matrix of B, then matrix A* is a quasi-optimal transfer matrix of A and is consistent.

$$A^* = 10C \tag{16}$$

According to Theorem 2, matrix A is its own quasi-optimal transfer matrix and is consistent. Therefore, the weight values can be directly derived from A without the need for consistency validation.

3.3.3. *Judgment matrix*

The judgment matrix A is constructed based on the importance ranking:

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1j} \\ a_{21} & a_{22} & \cdots & a_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ a_{i1} & a_{i2} & \cdots & a_{ij} \end{bmatrix} \tag{17}$$

where:
If $a_{ij} = 1$, it means that $i$is more important than j;
If $a_{ij} = 0$, it means that i and j are equally important;
If $a_{ij} = -1$, it means that j is more important than i.
The optimal transfer matrix for A is T.

$$T = \begin{bmatrix} t_{11} & t_{12} & \cdots & t_{1j} \\ a_{21} & a_{22} & \cdots & t_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ t_{i1} & t_{i2} & \cdots & t_{ij} \end{bmatrix} \tag{18}$$

Where,

$$t_{ij} = \frac{1}{n} \sum_{k=1}^{n} (a_{ik} - a_{ij}) \tag{19}$$

The judgment matrix derived from T is:

$$K = \begin{bmatrix} k_{11} & k_{12} & \cdots & k_{1j} \\ k_{21} & k_{22} & \cdots & k_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ k_{i1} & k_{i2} & \cdots & k_{ij} \end{bmatrix} \tag{20}$$

Where，

$$k_{ij} = \exp(x_{ij}) \tag{21}$$

The weights of each evaluation indicator can be directly calculated using the following formula:

$$W = \left[w_1, w_2, w_3, \cdots, w_i \right]^T \tag{22}$$

$$W_i = \frac{\sqrt[n]{\prod_{m=1}^{n} k_{ij}}}{\sum_{m=1}^{n} \sqrt[n]{\prod_{m=1}^{n} k_{im}}} \tag{23}$$

4. Results

4.1. *Judgment Matrix and Indicator Weights*

To ensure the scientific rigor of the evaluation weights, this study invited ten experts with extensive experience in sediment dredging and aquatic ecological restoration to systematically determine the order of relative importance for the evaluation indicators. Unlike the traditional method of absolute scoring, ranking by importance can more accurately capture the experts' logical consensus on the hazard levels of pollution factors, effectively reducing random fluctuations inherent in individual expert scoring.
Based on the sediment pollution characteristics of the coal mining subsidence area in Suzhou City and previous research findings, the expert panel ranked the order of importance at each level of the evaluation system as follows:

At the criterion layer, the order of importance is: Heavy Metals > Nutrients and Organic Matter. At the indicator layer, the order of importance is: TP > TN > OM; Mercury > Cadmium > Chromium > Arsenic > Lead = Copper = Nickel > Zinc. The judgment matrix was constructed according to this order of importance.

4.1.1. *Construct the Judgment Matrix*

The judgement matrix for control factors at the guideline level is as follows:

$$A = [A_i] = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$$

The judgement matrix for control factors at the indicator level is as follows:

$$A_{1j} = \begin{bmatrix} 0 & -1 & 1 \\ 1 & 0 & 1 \\ -1 & -1 & 0 \end{bmatrix}$$

$$A_{2j} = \begin{bmatrix} 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ -1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 \\ -1 & -1 & 0 & 1 & 1 & 1 & -1 & 1 \\ -1 & -1 & -1 & 0 & 0 & 0 & -1 & 1 \\ -1 & -1 & -1 & 0 & 0 & 0 & -1 & 1 \\ -1 & -1 & -1 & 0 & 0 & 0 & -1 & 1 \\ -1 & -1 & 1 & 1 & 1 & 1 & 0 & 1 \\ -1 & -1 & -1 & -1 & -1 & -1 & -1 & 0 \end{bmatrix}$$

4.1.2. Optimal Transfer Matrix

Calculate the optimal transfer matrix of the judgement matrix based on Equation (19).The optimal transfer matrix for the control factors in the criterion layer is

$$T_i = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$$

The optimal pass-through matrix for control factors in the indicator layer is

$$T_{1j} = \begin{bmatrix} 0.000 & -0.667 & 0.667 \\ 0.667 & 0.000 & 1.333 \\ -0.667 & -1.333 & 0.000 \end{bmatrix}$$

$$T_{2j} = \begin{bmatrix} 0.00 & 0.25 & 0.75 & 1.25 & 1.25 & 1.25 & 0.50 & 1.75 \\ -0.25 & 0.00 & 0.50 & 1.00 & 1.00 & 1.00 & 0.25 & 1.50 \\ -0.75 & -0.50 & 0.00 & 0.50 & 0.50 & 0.50 & -0.25 & 1.00 \\ -1.25 & -1.00 & -0.50 & 0.00 & 0.00 & 0.00 & -0.75 & 0.50 \\ -1.25 & -1.00 & -0.50 & 0.00 & 0.00 & 0.00 & -0.75 & 0.50 \\ -1.25 & -1.00 & -0.50 & 0.00 & 0.00 & 0.00 & -0.75 & 0.50 \\ -0.05 & -0.25 & 0.25 & 0.75 & 0.75 & 0.75 & 0.00 & 1.25 \\ -1.75 & -1.25 & -1.00 & -0.50 & -0.50 & -0.50 & -1.25 & 0.00 \end{bmatrix}$$

Determining the decision matrix for the optimal transfer matrix. Calculate the decision matrix for the optimal transfer matrix based on Equation (21).The decision matrix for the control factors within the criterion layer is:

$$K_i = \begin{bmatrix} 1.0000 & 0.3679 \\ 2.7183 & 1.0000 \end{bmatrix}$$

The judgement matrix for control factors at the indicator level is as follows:

$$K_{1j} = \begin{bmatrix} 1.0000 & 0.5134 & 1.9477 \\ 1.9477 & 1.0000 & 3.7937 \\ 0.5134 & 0.2636 & 1.0000 \end{bmatrix}$$

$$K_{2j} = \begin{bmatrix} 1.0000 & 1.2840 & 2.1170 & 3.4903 & 3.4903 & 3.4903 & 1.6487 & 5.7546 \\ 0.7788 & 1.0000 & 1.6487 & 2.7183 & 2.7183 & 2.7183 & 1.2840 & 4.4817 \\ 0.4724 & 0.6065 & 1.0000 & 1.6487 & 1.6487 & 1.6487 & 0.7788 & 2.7183 \\ 0.2865 & 0.3679 & 0.6065 & 1.0000 & 1.0000 & 1.0000 & 0.4724 & 1.6487 \\ 0.2865 & 0.3679 & 0.6065 & 1.0000 & 1.0000 & 1.0000 & 0.4724 & 1.6487 \\ 0.2865 & 0.3679 & 0.6065 & 1.0000 & 1.0000 & 1.0000 & 0.4724 & 1.6487 \\ 0.6065 & 0.7788 & 1.2840 & 2.1170 & 2.1170 & 2.1170 & 1.0000 & 3.4903 \\ 0.1738 & 0.2231 & 0.3679 & 0.6065 & 0.6065 & 0.6065 & 0.2865 & 1.0000 \end{bmatrix}$$

4.1.3. *Indicator Weights*

Calculate the theoretical weight values of the control factors based on Equation (23). The theoretical weight values of the control factors in the criterion layer are

$$W_i = [0.2689, 0.7311]$$

The theoretical weighting value of the controlling factors in the indicator layer is

$$W_{1j} = [0.3072, 0.5065, 0.1863]$$
$$W_{2j} = [0.4042, 0.2452, 0.0902, 0.0332, 0.0332, 0.0332, 0.1487, 0.0122]$$

In summary, the overall ranking parameters for the ecological risk levels of river and lake sediment dredging are presented in Table 7.

Table 7: Calculation of the Overall Ranking Parameters for the Ecological Risk Hierarchy of River and Lake Sediment Dredging

Goal Layer	Criteria Layer		Indicator Layer	
	Elements	**Weights**	**Elements**	**Weights**
Ecological Risk Assessment of Sediment	Nutrient Salts and Organic Matter	0.2689	TN	0.083
			TP	0.136
			OM	0.050
	Heavy Metals	0.7311	Mercury	0.295
			Cadmium	0.179
			Arsenic	0.066
			Lead	0.024
			Copper	0.024
			Nickel	0.024
			Chromium	0.109
			Zinc	0.09

4.2. *Evaluation Results*

Building upon the single-indicator calculation method outlined in Section 3 and the indicator weights determined in Section 4.1, an ecological risk assessment of the river and lake sediments was conducted for the water diversion project in the coal mining subsidence areas of the Zhuxianzhuang and Luling Mines in Yongqiao District, Suzhou City, Anhui Province. This analysis evaluates the overall condition of the sediments in the region.

By substituting the average values of indicators from the six sampling points in the Zhuxianzhuang mining area into the sediment ecological risk evaluation system, the assessment results are presented in Table 8. The results indicate that the comprehensive risk score for the sediments in the Zhuxianzhuang mining area is 3.90, placing it overall in a state of mild risk. Although the comprehensive score falls within the safe range, a deeper analysis of individual indicators reveals that the scores for Total Nitrogen (TN) and Mercury (Hg) are only 3 points, indicating a pollution level approaching moderate. This suggests that while the total heavy metal content in the area has not yet exceeded standards comprehensively, the specific enrichment trend of mercury already constitutes a potential ecological threat. Consequently, during the construction of the purification ponds, the dredging engineering strategy should shift from traditional large-scale dredging to the targeted removal of surface sediments rich in mercury and nitrogen. This optimized approach can not only effectively intercept internal pollution sources but also, in practical engineering terms, reduce ineffective earthwork volume and save costs. It thereby provides an implementation pathway for regional ecological restoration that balances scientific rigor with economic efficiency.

Based on the average values of indicators from the 11 sampling points in the Luling mining area, these were incorporated into the ecological risk assessment system for dredged sediments. The evaluation results are presented in Table 9. The comprehensive risk score for sediments in the Luling mining area is 3.98 points, also rated as mild risk, with its overall ecological quality indicators slightly superior to those of the Zhuxianzhuang mining area. Notably, although the number of sampling points in the Luling mining area increased to 11, its evaluation results exhibited high spatial stability compared to the Zhuxianzhuang mining area. This phenomenon validates the applicability of the assessment framework within the specific ecological unit of the coal mining subsidence area. In the detailed indicator analysis, the total phosphorus (TP) score in the Luling mining area was 4 points, indicating relatively good performance, which reflects the differentiated pollution characteristics across different mining areas. Based on these evaluation results, engineering decisions can adopt a risk benchmarking management model. Building upon the targeted dredging approach in Zhuxianzhuang, the construction schedule can be optimized according to the specific distribution patterns of nitrogen and mercury in the Luling mining area. Such a regionally coordinated governance plan, grounded in quantitative scoring, ensures that the dredging project across the entire area achieves ecological objectives while attaining higher cost-efficiency benefits.

Table 8: Comprehensive Ecological Risk Assessment Results of Dredged Sediment in Zhuxianzhuang Mining Area

Criteria Layer	Indicator Layer (mg/kg)	Indicator Value	Indicator Score	Overall Score
Nutrient Salts	Total Nitrogen	817	3	3.90
	Total Phosphorus	467	4	
	Organic Matter	8.35	5	
Heavy Metals	Copper	21.667	5	
	Zinc	59.333	5	
	Nickel	32	4	
	Chromium	59.833	5	
	Lead	15.917	5	
	Cadmium	0.0667	4	
	Mercury	0.1285	3	
	Arsenic	3.798	5	

The ecological risk assessment results for the dredged sediments at each sampling point are shown in Figure 3. The assessment outcomes display significant spatial regularity. With the exception of sampling point Luling-1, the comprehensive scores of the remaining 16 points remain consistently above 3.7 points. This indicates a relatively low overall pollution load in the sediments of the project area, with the ecological risk associated with dredging activities being within a controllable range. These findings further corroborate the earlier judgment regarding the homogeneity of the sediment deposition environment. However, the performance score for point Luling-1 is significantly below the average, suggesting the presence of a localized pollution hotspot within this area. For such high-risk points, a generalized shallow dredging approach is unsuitable. Instead, a “complete removal + focused monitoring” strategy should be implemented. It is imperative to prevent such high-risk sediments from entering subsequent resource utilization processes to avoid the circulation of heavy metals within the ecological chain. Concurrently, vertical distribution profiling for key factors like mercury and phosphorus at this point should be conducted to scientifically define the depth of contamination, enabling precise delineation of the dredging boundary. The results of this sediment ecological risk assessment provide quantitative safeguards for mitigating secondary environmental risks in large-scale water conservancy projects. They hold substantial theoretical and practical significance for constructing a multi-objective, coordinated dredging assessment framework and advancing the sustainable development of the water environment.

Table 9: Comprehensive Ecological Risk Assessment Results of Dredged Sediment in Luling Mining Area

Criteria Layer	Indicator Layer (mg/kg)	Indicator Value	Indicator Score	Overall Score
Nutrient Salts	Total Nitrogen	637.273	4	3.98
	Total Phosphorus	426.273	4	
	Organic Matter	9.436	5	
Heavy Metals	Copper	21.000	5	
	Zinc	55.182	5	
	Nickel	31.364	4	
	Chromium	62.182	5	
	Lead	15.873	5	
	Cadmium	0.055	5	
	Mercury	0.112	3	
	Arsenic	5.439	5	

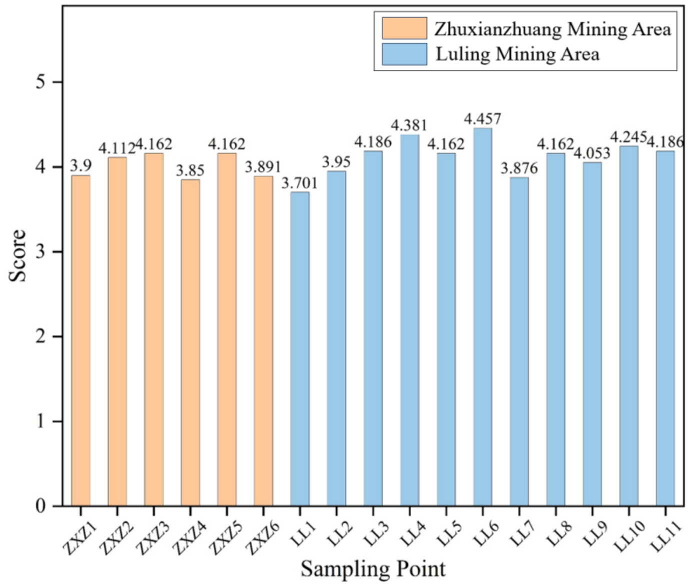

Figure 2: Ecological Risk Assessment Results of Sediment at Each Sampling Point

4.3. *Comparative Validation of the Improved AHP Method and Traditional AHP Method*

To verify the scientific validity of the AHP method improved by the Optimal Transfer Matrix, this study employed the traditional AHP method as a control. Using the same set of expert scoring data for parallel computation, a comparison was conducted to validate the accuracy and advantages of the improved AHP method.

4.3.1. *Comparison of Indicator Weights*

As shown in Table 10, comparing the indicator weights calculated by the two methods reveals that the weight rankings obtained from both are completely consistent. At the criterion layer, both methods show Heavy Metals > Nutrients and Organic Matter. Within the heavy metal sequence at the indicator layer, Hg and Cd consistently occupy the top two weight positions, and the weight ranking of the remaining indicators aligns with that calculated by the traditional AHP method. In the nutrient sequence, TP holds the highest weight, and the ranking of TN and OM indicator weights is consistent. The consistency in indicator weight ranking demonstrates that the improved AHP method fully inherits the traditional AHP method's capability to identify core indicators, ensuring the scientific nature and logical coherence of the evaluation direction.

Comparing the specific numerical values reveals that the manual adjustments made in the traditional AHP method to pass the consistency check often lead to a tendency for weight distribution to become more averaged; that is, high weights are suppressed and low weights are elevated, resulting in a phenomenon of weight dilution. As shown in Table 10 below, the weights for Hg (0.295) and Cd (0.179) calculated by the improved AHP method are approximately 46% and 25% higher, respectively, compared to those from the traditional AHP method (0.1598, 0.1334). The improved AHP method is more sensitive in capturing highly toxic and high-risk factors, more accurately reflecting the experts' focus on core risk points, and effectively avoids risk underestimation caused by methodological shortcomings.

The root cause of this weight discrepancy lies in the mathematical mechanism of the Optimal Transfer Matrix. This method generates a completely consistent quasi-optimal matrix by finding the optimal transitive form of the original judgment matrix, thereby avoiding the artificial, subjective iterative adjustment process. Consequently, it better preserves the relative importance information contained in the experts' initial judgments.

Table 10: Comparison of indicator weights before and after improvement

Criteria Layer			Indicator Layer		
Elements	Improved Weights	Weight before improvement	Elements	Improved Weights	Weight before improvement
Nutrient Salts and Organic Matter	0.2689	0.3333	TN	0.083	0.1002
			TP	0.136	0.1601
			OM	0.050	0.0731
Heavy Metals	0.7311	0.6667	Mercury	0.295	0.1598
			Cadmium	0.179	0.1334
			Arsenic	0.066	0.0831
			Lead	0.024	0.0506
			Copper	0.024	0.0506
			Nickel	0.024	0.0506
			Chromium	0.109	0.1020
			Zinc	0.009	0.0366

4.3.2. *Comparison of Evaluation Results*

A comparison of the comprehensive risk scores for each sampling point, calculated using the two methods, is presented in Table 11. The specific data reveals that the evaluation results obtained from the two methods are highly consistent in their overall trend. The risk scores for the 17 sampling points calculated by both methods exhibit a strong positive correlation, indicating that the improved method does not alter the overall pattern of spatial risk distribution, thereby validating the reliability of its assessment results.

Comparing the evaluation results before and after the improvement, it can be observed that the risk scores from the improved AHP method are slightly higher than or equal to those from the traditional method at the vast majority of sampling points, with an average increase of approximately 0.08 points. This systematic upward shift directly stems from the increased weights of the core heavy metals (Hg, Cd), allowing the contribution of heavy metal pollution to be more fully accounted for in the total score. Most crucially, the risk level for sampling point LL1 was adjusted from "Moderate Pollution" to "Mild Pollution". This change suggests that the traditional method may have overestimated the risk level at this point due to weight dilution, whereas the improved method provides a more precise differentiation, avoiding potential decisions for excessive dredging, thereby aiding in the optimization of resource allocation.

In summary, the improvement of AHP by the optimal transfer matrix method eliminates the tedious and subjective cycle of consistency checking and adjustment required in traditional AHP, rendering the weight calculation process entirely procedural and objective, thereby enhancing assessment efficiency and reproducibility. The risk reclassification of sampling point LL1 demonstrates that the improved method possesses a finer risk discrimination capability in critical zones, offering a more reliable basis for differentiated and precise environmental management. It provides a more dependable and efficient methodological tool for the scientific decision-making and risk control of dredging projects.

Table 11: Comprehensive evaluation results of each sampling point before and after improvement

Number	Score Before Improvement	Score After Improvement
ZXZ1	3.88	3.90
ZXZ2	3.88	4.11
ZXZ3	4.11	4.16
ZXZ4	3.81	3.85
ZXZ5	4.11	4.16
ZXZ6	4.00	3.89
LL1	3.47	3.70
LL2	3.89	3.95
LL3	4.16	4.19
LL4	4.37	4.38
LL5	4.11	4.16
LL6	4.27	4.46
LL7	3.83	3.88
LL8	4.11	4.16
LL9	3.99	4.05
LL10	4.21	4.25
LL11	4.16	4.19

5. Discussion

5.1. *Analysis of Regional Representativeness and Limitations of Sampling Scale*

This study constructed a risk assessment framework based on a total of 17 sediment samples from the Zhuxianzhuang mining area (6 points) and the Luling mining area (11 points), which is reasonable within the specific geographical context of this research. Coal mining subsidence areas constitute relatively enclosed artificial hydraulic units with weak hydrodynamics, leading to relatively stable and continuous sediment deposition processes. According to statistical results (see Table 1), except for Cd, the coefficients of variation (CV) for other indicators all fall within the low range of 16%–33%. This phenomenon indicates a relatively uniform distribution of pollutants within the region, and the existing sampling points are sufficient to capture the core risk characteristics of the project area. However, as a preliminary evaluation framework, this study acknowledges its limitations in spatial coverage. Future research could incorporate geostatistical simulations to further validate the framework's generalizability in extremely large mining areas or open river-lake systems.

5.2. *Advantages of the Improved AHP Model*

This study achieved a mathematical mapping from empirical ranking to scientific weights through the optimal transfer matrix. When dealing with 11 indicators, the traditional AHP often encounters difficulty in passing the consistency test for its judgment matrix, forcing evaluators to make artificial adjustments. In contrast, the core advantages of the method used in this study are:

(1) It directly generates a consistent matrix through analytical derivation, fundamentally eliminating the secondary subjective interference present in the traditional method where data is adjusted to force consistency.

(2) The model fully preserves the original judgment of experts regarding the importance ranking of key factors like Hg and TP, resolving logical contradictions through mathematical smoothing rather than human intervention. This mode, which combines qualitative expert ranking with quantitative model mapping, enhances the academic rigor of the evaluation process while ensuring engineering experience is respected.

5.3. *Relevance of Evaluation Results to Practical Engineering Recommendations*

The comprehensive risk assessment results of this study indicate that both the Zhuxianzhuang mining area (score: 3.90) and the Luling mining area (score: 3.98) are at a Mild Risk level. Despite the relatively high overall scores, the lower individual scores for TN and Hg indicate specific environmental pressures within the sediments. Based on the quantitative scoring from this study, it is recommended that the engineering implementation adopt layered, targeted dredging. Surface sediments enriched with Hg should be mandatorily removed, while deeper sediments that meet standards could be treated with in-situ capping or ecological solidification. This approach aims to reduce environmental risk while optimizing the project budget through precise construction practices.

6. Conclusions

This study established an ecological risk assessment system for river and lake sediment dredging based on the Analytic Hierarchy Process (AHP). Through a hierarchical classification approach, it systematically evaluated a total of 11 indicators, including total nitrogen, total phosphorus, organic matter, and 8 heavy metals. Combined with expert importance ranking, this system can comprehensively and quantitatively reflect pollution levels, providing a structured assessment framework for dredging projects.

To overcome the issue in traditional AHP where weight calculation is susceptible to subjective adjustment, this study applied the optimal transfer matrix to improve AHP. This method directly generates a consistent matrix through a mathematical mechanism, eliminating the need for repeated consistency checks and manual corrections, thereby enhancing the objectivity and computational efficiency of weight determination. Weight analysis indicates that heavy metal pollution contributes the most (total weight: 0.7311), with mercury (0.295), cadmium (0.179), and chromium (0.109) having the most significant influence. Among nutrients, total phosphorus holds the highest weight (0.136).

Applying the improved method to case assessments in the Zhuxianzhuang and Luling mining areas of Suzhou City, Anhui Province, yielded the following results: the average comprehensive risk score for the 6 sampling points in the Zhuxianzhuang mining area was 3.90, and for the 11 points in the Luling mining area was 3.98. Sediments in both areas are at a Mild Pollution level. The main risk factors are total nitrogen (Zhuxianzhuang: 817 mg/kg, Luling: 637.27 mg/kg) and mercury (Zhuxianzhuang: 0.1285 mg/kg, Luling: 0.112 mg/kg), which should be given particular attention during dredging.

(4)By applying the improved AHP method to sediment ecological risk assessment, this study verified its practical value in enhancing weight consistency and reducing subjective bias. This assessment system can provide a quantitative basis for determining dredging priorities, implementing zonal management, and promoting the resource utilization of river and lake sediments. It holds significant theoretical and practical implications for advancing refined management and the sustainable development of the water environment.

Author Contribution
Huaqing Zhang: Formal analysis, Writing – original draft.
Lei Li: Conceptualization, Funding acquisition, Project administration.
Hui Qiu: Data curation.
Junhao Chen: Validation
Wenran Chen: Writing – review & editing

Funding
This research work was jointly supported by the National Key R&D Program of China (Project No.: 2022YFC3202704) and the Water Conservancy Science and Technology Project of Jiangsu Province (no. 2024046).

References

1. Ashour, M., & Mahdiyar, A. (2024). A comprehensive state-of-the-art survey on the recent modified and hybrid analytic hierarchy process approaches. *Applied Soft Computing, 150*, 111014. https://doi.org/10.1016/j.asoc.2023.111014
2. Bose A. (2020a). Using genetic algorithm to improve consistency and retain authenticity in the analytic hierarchy process. *OPSEARCH, 57*(4): 1070-1092. https://doi.org/10.1007/s12597-020-00450-z
3. Bose A. (2020b). Using genetic algorithm to improve consistency and retain authenticity in the analytic hierarchy process. *OPSEARCH, 57*(4): 1070-1092. https://doi.org/10.1007/s12597-020-00450-z
4. Bose A. (2022). Consistency re-evaluation in analytic hierarchy process based on simulated consistent matrices. *Journal of Multi-Criteria Decision Analysis, 29*(5-6): 393-401. https://doi.org/10.1002/mcda.1784
5. Dai T., Wang L., Li T., Qiu P., Wang J., & Song H. (2023). Potential linkage between WWTPs-river-integrated area pollution risk assessment and dissolved organic matter spectral index. *Environmental Geochemistry and Health, 45*(8): 6693-6711. https://doi.org/10.1007/s10653-023-01637-1
6. Ferrans L., Jani Y., Burlakovs J., Klavins M., & Hogland W. (2021). Chemical speciation of metals from marine sediments: Assessment of potential pollution risk while dredging, a case study in southern Sweden. *Chemosphere, 263*: 128105. https://doi.org/10.1016/j.chemosphere.2020.128105
7. Gastes D., & Gaul W. (2012). The Consistency Adjustment Problem of AHP Pairwise Comparison Matrices//Diamantopoulos A, Fritz W, Hildebrandt L. *Quantitative Marketing and Marketing Management. Wiesbaden: Gabler Verlag*: 51-62. https://doi.org/10.1007/978-3-8349-3722-3_2
8. Gursoy, B. B., Mason, O., & Sergeev, S. (2013). The analytic hierarchy process, max algebra and multi-objective optimisation. *Linear Algebra and its Applications, 438*(7): 2911-2928. https://doi.org/10.1016/j.laa.2012.11.020
9. Herath, I. K., Wu, S., Ma, M., & Ping, H. (2022). Heavy metal toxicity, ecological risk assessment, and pollution sources in a hydropower reservoir. *Environmental Science and Pollution Research International, 29*(22): 32929-32946. https://doi.org/10.1007/s11356-022-18525-3
10. Hseu Z Y. (2020). Ecological and Health Risk of Soils, Sediments, and Water Contamination. *Water, 12*(10): 2867. https://doi.org/10.3390/w12102867
11. Ishizaka, A., & Labib, A. (2009). Analytic Hierarchy Process and Expert Choice: Benefits and limitations. *OR Insight, 22*(4): 201-220. https://doi.org/10.1057/ori.2009.10
12. Kabenla, R., Ampofo, S., Owusu, G., Atulley, J. A., & Ampadu, B. (2024). Application of Analytical Hierarchy Process (AHP) and Multi-Criteria Evaluation (MCE) for a case study and scenario assessment of flood risk in the White Volta Basin of the Upper East Region, Ghana. *Discover Water, 4*(1): 90. https://doi.org/10.1007/s43832-024-00143-4

13. Karr, J. R., Soule, M. E., & Wilcox, B. A. (1981). Conservation Biology: An Evolutionary-Ecological Perspective. *The Journal of Wildlife Management, 45*(2): 567. https://doi.org/10.2307/3807953
14. Kong, F., & Liu, H. (2005). An Improvement on Saaty's AHP//Li D, Wang B. Artificial Intelligence Applications and Innovations: Vol. 187. New York: Springer-Verlag: 301-312. https://doi.org/10.1007/0-387-29295-0_32
15. Li, X., Liu, X., Huang, Y., Zhang, Y., & Li, J. (2024). Seasonal impact of constructed wetlands on nitrogen and phosphorus in sediments of flood control lakes with pollution assessment. *Journal of Environmental Quality, 53*(3): 340-351. https://doi.org/10.1002/jeq2.20561
16. Li, Y.-L., He, W., Liu, W.-X., Kong, X.-Z., Yang, B., Yang, C., & Xu, F.-L. (2015). Influences of binding to dissolved organic matter on hydrophobic organic compounds in a multi-contaminant system: Coefficients, mechanisms and ecological risks. *Environmental Pollution (Barking, Essex: 1987), 206*: 461-468. https://doi.org/10.1016/j.envpol.2015.07.047
17. Li J., Hu X., Zhang Y., Deng X., Qi Y., & Hao C (2025). Fuzzy-improved AHP evaluation of ecological restoration schemes: A case study of Panshitou Reservoir. *Journal of Henan Polytechnic University (Natural Science), 44*(4): 134-141. https://doi.org/10.16186/j.cnki.1673-9787.2023060035
18. Liu, Y., Eckert, C. M., & Earl, C. (2020). A review of fuzzy AHP methods for decision-making with subjective judgements. *Expert Systems with Applications, 161*: 113738. https://doi.org/10.1016/j.eswa.2020.113738
19. Manap, N., & Voulvoulis, N. (2015). Environmental management for dredging sediments - the requirement of developing nations. *Journal of Environmental Management, 147*: 338-348. https://doi.org/10.1016/j.jenvman.2014.09.024
20. Peláez, J. I., & Lamata, M. T. (2003). A new measure of consistency for positive reciprocal matrices. *Computers & Mathematics with Applications, 46*(12): 1839-1845. https://doi.org/10.1016/S0898-1221(03)90240-9
21. Ren S., Feng D., & Chen X (2017). Grey analytic hierarchy process using optimal transfer matrix. *Computer Engineering and Applications, 53*(18):44-50. http://www.cnki.net/kcms/detail/11.2127.TP.20160822.1010.040.html
22. Şener, E., Şener, Ş., & Bulut, C. (2023). Assessment of heavy metal pollution and quality in lake water and sediment by various index methods and GIS: A case study in Beyşehir Lake, Turkey. *Marine Pollution Bulletin, 192*: 115101. https://doi.org/10.1016/j.marpolbul.2023.115101
23. Shou, Y., Zhao, J., Zhu, Y., Qiao, J., Shen, Z., Zhang, W., Han, N., & Núñez-Delgado, A. (2022). Heavy metals pollution characteristics and risk assessment in sediments and waters: *The case of Tianjin, China. Environmental Research, 212*: 113162. https://doi.org/10.1016/j.envres.2022.113162
24. Soetan, O., Nie, J., & Feng, H. (2022). Preliminary environmental assessment of metal-contaminated sediment dredging in an Urban River, New Jersey, USA. *Marine Pollution Bulletin, 184*: 114212. https://doi.org/10.1016/j.marpolbul.2022.114212
25. Wang, M., Liu, J., & Lai, J. (2019). Metals Pollution and Ecological Risk Assessment of Sediments in the Poyang Lake, China. *Bulletin of Environmental Contamination and Toxicology, 102*(4): 511-518. https://doi.org/10.1007/s00128-019-02577-2
26. Wang Y J. (2015). Ranking triangle and trapezoidal fuzzy numbers based on the relative preference relation. *Applied Mathematical Modelling, 39*(2): 586-599. https://doi.org/10.1016/j.apm.2014.06.011
27. Wen, Y.-W., Li, K., & Chen, H. (2023). Accelerated matrix completion algorithm using continuation strategy and randomized SVD. *Journal of Computational and Applied Mathematics, 429*: 115215. https://doi.org/10.1016/j.cam.2023.115215
28. Weng J X. (2017). Post-dredging effect assessment based on sediment chemical quality in urban rivers of Yangzhou. *Environmental Monitoring and Assessment, 189*(6): 246. https://doi.org/10.1007/s10661-017-5963-x

29. Wu, S.-H., Xiang, H.-C., He, B., Liu, X.-D., & Fan, Q.-J. (2026). A novel approach for detecting and adjusting inconsistencies in AHP models. *Journal of Control and Decision, 0*(0): 1-17. https://doi.org/10.1080/23307706.2025.2605268
30. Wu, T., Qin, B., Brookes, J. D., Yan, W., Ji, X., & Feng, J. (2019). Spatial distribution of sediment nitrogen and phosphorus in Lake Taihu from a hydrodynamics-induced transport perspective. *The Science of the Total Environment, 650*(Pt 1): 1554-1565. https://doi.org/10.1016/j.scitotenv.2018.09.145
31. Wu, Z., Rao, W., Zheng, F., Zhang, C., & Li, T. (2023). Pollution source identification of nitrogen and phosphorus in the lower West Main Canal, the Ganfu Plain irrigation district (South China). *Environmental Monitoring and Assessment, 195*(8): 1011. https://doi.org/10.1007/s10661-023-11641-8
32. Xiang, M., Li, Y., Yang, J., Lei, K., Li, Y., Li, F., Zheng, D., Fang, X., & Cao, Y. (2021). Heavy metal contamination risk assessment and correlation analysis of heavy metal contents in soil and crops. *Environmental Pollution (Barking, Essex: 1987), 278*: 116911. https://doi.org/10.1016/j.envpol.2021.116911
33. Xie, Q. M., & Xia, Y. Y. (2004). A multi-objective decision-making method for the treatment scheme of landslide hazard. *Journal of University of Science and Technology Beijing, 11*(2): 101-105.
34. Yan, J., & Li, F. (2023). Effects of sediment dredging on freshwater system: a comprehensive review. *Environmental Science and Pollution Research International, 30*(57): 119612-119626. https://doi.org/10.1007/s11356-023-30851-8
35. Yang, C., Zeng, Z., Wang, Y., He, G., Hu, Y., Gao, D., Dai, Y., Li, Q., & Zhang, H. (2023). Ecological risk assessment and identification of the distinct microbial groups in heavy metal-polluted river sediments. *Environmental Geochemistry and Health, 45*(5): 1311-1329. https://doi.org/10.1007/s10653-022-01343-4
36. Yang, P., Yang, C.-H., Ma, X.-Y., & Yin, H.-B. (2021).. Sediment Pollution Characteristics and Dredging in the Nanfei River Estuary, Chaohu Lake. *Environmental Science, 42*(2): 712-722. https://doi.org/10.13227/j.hjkx.202005320
37. Yang, X., Zhong, M., Pu, J., Liu, C., Luo, H., & Xu, M. (2022). Risk control and assessment of sulfide-rich sediment remediation by controlled-release calcium nitrate. *Water Research, 226*: 119230. https://doi.org/10.1016/j.watres.2022.119230
38. Ye, H., Huang, C., Yuan, X., Wang, H., Huang, T., & Yang, H. (2021). Morphological characteristics and ecological risk assessment of nitrogen and phosphorus in the sediments of Futunxi watershed in Fujian province. *Environmental Monitoring and Assessment, 193*(6): 335. https://doi.org/10.1007/s10661-021-09106-x
39. Yin Z. (2023). The pollution of microplastics in sediments: The ecological risk assessment and pollution source analysis. *Science of The Total Environment, 859*: 160323. https://doi.org/10.1016/j.scitotenv.2022.160323
40. Yuan, L.-B., Xing, S.-Y., Liu, X., Zhou, X.-H., & Adelaida, A. D. (2021). Distribution Characteristics and Pollution Evaluation of Nitrogen and Organic Matter in Overlying Water and Sediment of Guyun River and Jinshan Lake in Zhenjiang City. *Environmental Science, 42*(7): 3186-3197. https://doi.org/10.13227/j.hjkx.202010192
41. Zhang, S., Zeng, X., Sun, P., & Ni, T. (2023). Ecological risk characteristics of sediment-bound heavy metals in large shallow lakes for aquatic organisms: *The case of Taihu Lake, China. Journal of Environmental Management, 342*: 118253. https://doi.org/10.1016/j.jenvman.2023.118253
42. Zhong, C., Yang, Q., Liang, J., & Ma, H. (2022a). Fuzzy comprehensive evaluation with AHP and entropy methods and health risk assessment of groundwater in Yinchuan Basin, northwest China. *Environmental Research, 204*(Pt A): 111956. https://doi.org/10.1016/j.envres.2021.111956
43. Zhong, C., Yang, Q., Liang, J., & Ma, H. (2022b). Fuzzy comprehensive evaluation with AHP and entropy methods and health risk assessment of groundwater in Yinchuan Basin, northwest China. *Environmental Research, 204*(Pt A): 111956. https://doi.org/10.1016/j.envres.2021.111956

44. Zyoud, S., Omair, S. M., & Jarrad, S. A. (2025). A two-stage model of the fuzzy analytic hierarchy process and the fuzzy synthetic evaluation technique to prioritize sustainable sanitation services under uncertainty. *Scientific Reports, 15*(1): 3736. https://doi.org/10.1038/s41598-025-88236-5