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EDITED BY
Zhi Wang,
Chinese Academy of Sciences (CAS), China

REVIEWED BY
Bayram Yuksel,
Giresun University, Türkiye
Gordana Čanadi Jurešić,
University of Rijeka, Croatia

*CORRESPONDENCE
Chao Ji,
208860788@qq.com
Dawei Hou,
356052061@qq.com

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Source apportionment and ecological risk of heavy metals in Taihu lake from 2020 to 2022

Guangjing Bao[1], Chao Ji[2]*, Dawei Hou[3]*, Yuanbin He[1], Yan Li[1], Dongmei Lei[1] and Xi Fan[1]

[1]College of Logistics and Management Engineering, Yunnan University of Finance and Economics, Kunming, China, [2]College of Public Finance and Management, Yunnan University of Finance and Economics, Kunming, China, [3]College of Public Administration and Law, Northeast Agricultural University, Harbin, China

To determine the source apportionment and ecological risk of heavy metals in water from a spatiotemporal perspective, the 7 samples were monitored from 2020 to 2022 in Taihu Lake. The correlation analysis and principal component analysis were employed to identify the sources of heavy metals, and the temporal and spatial characteristics of ecological risk were analyzed using the Mann-Kendall test, mean gravity center, and standard-deviation ellipse. The results indicated an increase in median concentration of heavy metals in the following order: Cd < Pb < Hg < Cu < As < Ni < Zn, These metals were primarily derived from industrial and agricultural activities. Overall, the ecological risks posed by heavy metals were deemed acceptable, with the exception of Hg, which showed considerable potential ecological risk. Furthermore, the potential ecological risk exhibited a significant decreasing trend, with *Z*-values passing the 95% confidence interval significance test, except for S3. The mean gravity centers of the potential ecological risk were located within an ellipse with center coordinates of (120.2553, 31.3718), major axis of 44,525 m, minor axis of 28,225 m, and a direction of 0.4463°. This study contributes to the enrichment of research perspectives for ecological risk and provides valuable insights for the development of mitigation strategies for heavy metals in Taihu Lake.

KEYWORDS

water heavy metals, potential ecological risk, Mann-Kendall test, mean gravity center, standard-deviation ellipse

1 Introduction

Heavy metal contamination caused by intense anthropogenic perturbations is considered a troublesome problem due to its widespread distribution, long-lasting toxicity, and bio-accumulation (Zhao et al., 2020; Khanom and Hayashi, 2021; Xu et al., 2019). Extensive industrialization and urban sprawl can lead to the introduction of heavy metals into lakes, resulting in undesired environmental outcomes such as inhibiting plant photosynthesis, restraining animal growth, and threatening human health (Khanom and Hayashi, 2021; Bian et al., 2017; Uluturhan and Kucuksezgin, 2007; Xie et al., 2016). Therefore, it is essential to understand the characteristics, sources, and risks associated with heavy metals in water for proper function division, pollution prevention, and risk control.

In recent decades, the combination of natural factors and human activities, including industrial waste, sewage runoff, and agricultural discharge, has resulted in heavy metal pollution in water. (Ding et al., 2020; Wang and Zang, 2014; Zhang et al., 2020; Li Y. et al., 2020). For example, the total amount of wastewater discharged in China amounted to 73.53 billion tons, containing 3.59 billion tons in the Taihu Lake Basin in 2020. In order to reduce the harm caused by heavy metals to the aquatic environment, numerous studies have been implemented to address concerns regarding aquatic heavy metals over the past years, including ecological risk, resources, biological toxicity, and health risk (Li B. et al., 2020; Zhang et al., 2019; Xia et al., 2012). The content focuses on the monitoring, transfer, treatment, and risk assessment of heavy metals in water or sediment (Xu et al., 2019; Zhang et al., 2017; Biswal and Balasubramanian, 2023; Li et al., 2021), and the methods mainly include the enrichment factor, geo-accumulation index, contamination factor, potential ecological risk index, principal component analysis, and health risk assessment model (Zhao et al., 2020; Ji et al., 2021b; Rahman et al., 2014; Zhan et al., 2020). The current research perspective primarily concentrates on environmental science, while the continuous time variation characteristics analyzed from a geographical approach is relatively less explored.

Generally, Heavy metals entering the lake are difficult to be discharged in a short time due to the slower water velocity and longer water exchange recycle, and then the lake ecosystem is more susceptible to cumulative heavy metals, for instance, the heavy metal subsequently enter the aquatic flora, fauna, and microorganisms, of which some tissues are accumulated by heavy metals with several orders of magnitude higher than the corresponding background value of lakes after long-term exposure even at a low concentration level (Uluturhan and Kucuksezgin, 2007; Xia et al., 2020). Indeed, it is significantly important to explore the spatial-temporal variation characteristics for reducing the hazard of heavy metals by analyzing the sources and ecological risk of heavy metals in the water environment based on continuous time change from the perspective of geography (Ji et al., 2021a), especially for Taihu Lake with a complex aquatic ecosystem and a long history of anthropogenic impacts (Yuan et al., 2019).

Recently, various methods such as principal component analysis, correlation analysis, and positive matrix factorization have been employed to analyze the sources of heavy metals (Li Y. et al., 2020; Zhang et al., 2017; Fang et al., 2019). However, there is a lack of studies that analyzed the sources of heavy metals from the temporal perspective. Principal component analysis is commonly utilized to condense the original metal data into a minimal number of factors (Qiao et al., 2020). On the other hand, correlation analysis could analyze the degree of correlation between the heavy metals (Xiang et al., 1987). Considering that the sources of heavy metals in the lake environment may vary over time, a combination of qualitative and quantitative analysis is essential for effectively identifying these sources (Zhang et al., 2017; Niu et al., 2021). Therefore, principal component analysis and correlation analysis are critical and practical methods for investigating the long-term sources of heavy metals in Taihu Lake from 2020 to 2022. Additionally, the potential ecological risk index, which is based on theoretical water environment sedimentology (Hakanson, 1980), has been widely used by researchers worldwide to assess the ecological risks associated with heavy metals in lake sediments, including lakes like Taihu, Bourget, Poyang, Mariout, and Veeranam (Li Y. et al., 2020; Zhang et al., 2017; Abu El-Magd et al., 2021; Lécrivain et al., 2018; Suresh et al., 2012). In order to enhance its applicability to Taihu Lake, the parameters of the potential ecological risk index should be optimized, specifically the toxicity coefficient and classification criteria (Ma et al., 2020). Meanwhile, the Mann-Kendall test, also known as the distribution-free test, is a non-parametric statistical method used to determine the presence of significant temporal variations in variables such as vegetation, temperature, and precipitation (Kaushik et al., 2020; Rahman and Dawood, 2017; Yuan et al., 2020; Cavadias et al., 2002). And spatial-temporal characteristics of crop yield, climate variation, and economic development can be qualitatively assessed using methods such as the mean gravity center and standard-deviation ellipse (Balsa-Barreiro et al., 2019; Wang et al., 2020; Cao et al., 2021). The overall spatial-temporal variations of ecological risk posed by heavy metals in Taihu Lake could be effectively revealed by employing the Mann-Kendall test, mean gravity center, and standard-deviation ellipse.

Therefore, principal component analysis and correlation analysis were applied to analyze the sources of heavy metals in Taihu Lake from 2020 to 2022. Additionally, a modified potential ecological risk index was obtained to assess the potential threats posed by these metals. Furthermore, the Mann-Kendall test, mean gravity center, and standard-deviation ellipse were utilized to assess the spatial-temporal characteristics of ecological risk. The goals of this research were (a) to analyze the characteristics and possible sources of heavy metal elements (including As, Cd, Cu, Hg, Ni, Pb, and Zn) monitored in Taihu Lake from 2020 to 2022 and (b) to identify the spatial-temporal variation characteristics of ecological risk. To achieve these goals, a long-term monitoring study was conducted around Taihu Lake from 2020 to 2022, and the sources were investigated using correlation analysis and principal component analysis. In order to explore the ecological risk, the traditional potential ecological risk index proposed by Hakanson (1980) was optimized. Finally, the Mann-Kendall test, mean gravity center, and standard-deviation ellipse were employed to detect the spatial-temporal variation characteristics of ecological risk in Taihu Lake. This work aims to provide scientific evidence for risk management and pollution prevention in Taihu Lake and to enrich the researching perspective of heavy metals in water.

2 Materials and methods

2.1 Study area and sampling sites

Located on the southern edge of the Yangtze River Delta, Taihu Lake covers an approximate water area of 2,338 km^2 and has a subtropical monsoon climate with average precipitation ranging from 1,100 to 1,150 mm and temperatures ranging from 16.0°C to 18.0°C. The surrounding region of Taihu Lake comprises a network of water bodies, with hilly and mountainous terrain primarily located in the west and southwest, and plains dominating the

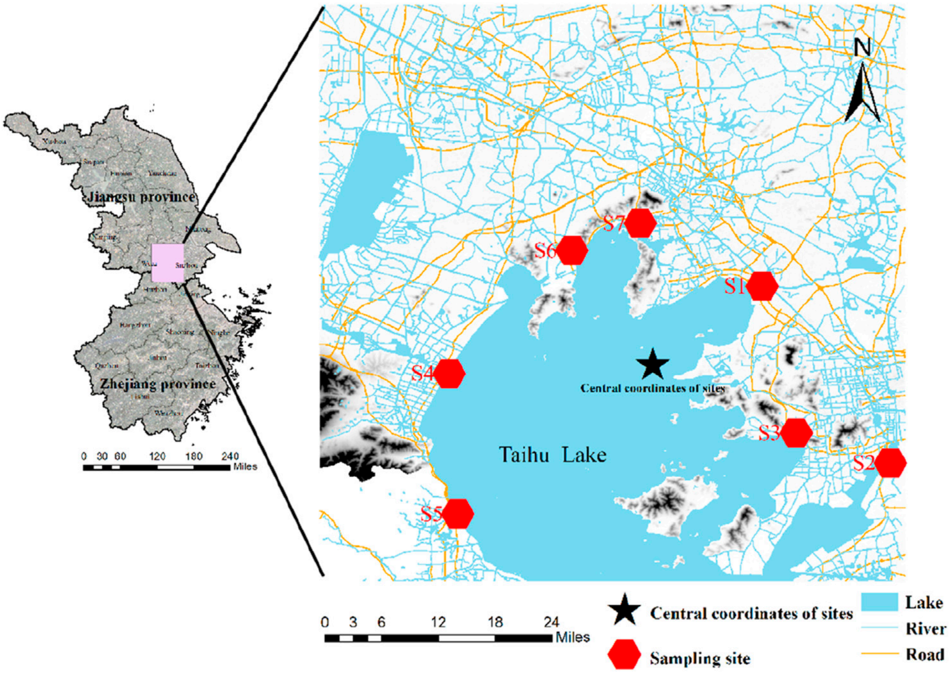

FIGURE 1
Location of sampling sites in the Taihu Lake (Revise).

TABLE 1 Comparative analysis of the ecological risk classification criteria between Hakanson's method and the approach proposed in this study.

The classification criteria	Hakanson	This research	Hakanson	This research
Low potential ecological risk	$E_r^i < 40$	$E_r^i < 30$	RI < 150	RI < 70
Moderate potential ecological risk	$40 \le E_r^i < 80$	$30 \le E_r^i < 60$	150 ≤ RI < 300	70 ≤ RI < 140
Considerable potential ecological risk	$80 \le E_r^i < 160$	$60 \le E_r^i < 120$	300 ≤ RI < 600	140 ≤ RI < 280
High potential ecological risk	$160 \le E_r^i < 320$	$100 \le E_r^i < 240$		280 ≤ RI < 560
Very high potential ecological risk	$E_r^i \ge 320$	$E_r^i \ge 240$	RI ≥ 600	RI ≥ 560

eastern area. Additionally, the northeast region is characterized by a high concentration of population and industrial production, while agricultural production is primarily distributed in the northwest. With the rapid industrialization and agricultural practices that have taken place since the 1980s, Taihu Lake has gradually become polluted. Furthermore, Taihu Lake plays a vital role as a water source for agricultural production and the wellbeing of the local population in China (Li Y. et al., 2020; Xia et al., 2012; Niu et al., 2020; Zhu, 2017; Zhang S. et al., 2018). Therefore, Understanding the migration mechanisms and the spatial-temporal characteristics of ecological risk of heavy metal in Taihu Lake is crucial for enhancing our comprehension of the stability of the lake ecosystem and providing valuable insights into the sustainable use of water. Seven sampling sites, positioned at the inlets of the main rivers of Taihu Lake, were chosen as the subjects of this study (Figure 1). Additionally, the sampling sites were evenly distributed around Taihu Lake and the central site, situated at coordinates (120.249571, 31.322114), served as the reference point for the sampling sites.

2.2 Samples measurement and analysis

The automatic monitoring instrument, based on anodic stripping voltammetry, was utilized to obtain electric signals indicative of heavy metal concentrations in the water environment. Through analysis and evaluation of these signals, the concentration of heavy metals in the water could be directly determined. The instrument effectively eliminated interference from organic matter during the monitoring process of surface water. In conjunction with the automatic water quality monitoring station, the automatic monitoring instrument was employed to monitor heavy metal concentrations at the sampling sites. The accuracy, precision, and detection limit of the monitoring data were ensured by checking the instrument's performance every 6 months. Additionally, instrument calibration was conducted monthly, following the regulations outlined in the Chinese technical specifications for automatic monitoring of surface water (HJ/T 91-2002). Meanwhile, the monitoring data from the sampling points were examined at least once every morning

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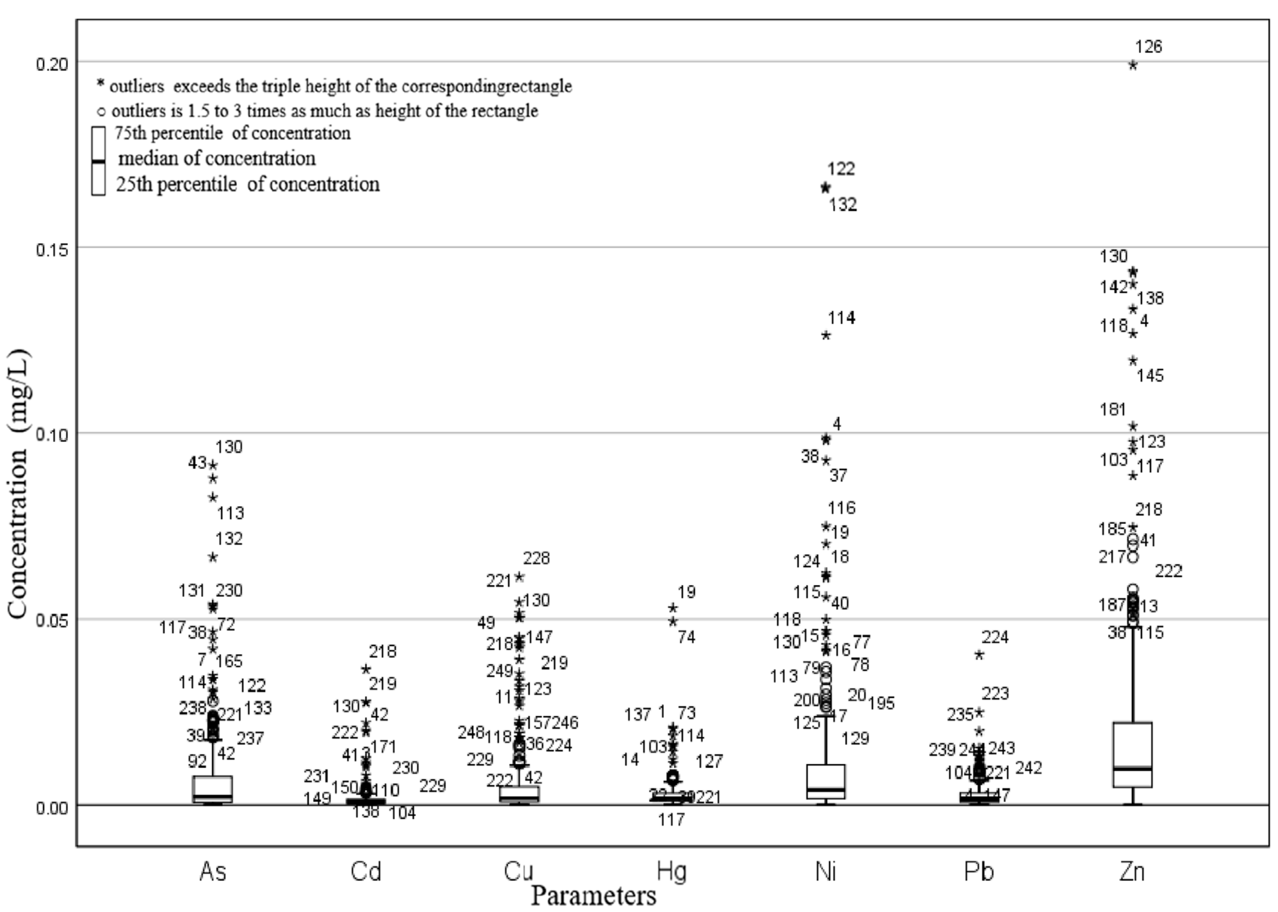

FIGURE 2
Boxplots of the heavy metal concentrations in sampling sites from 2020 to 2022.

TABLE 2 Pearson correlation matrix between heavy metals in Taihu Lake from 2020 to 2022.

Heavy metals	As	Cd	Cu	Hg	Ni	Pb	Zn
As	1						
Cd	0.162*	1					
Cu	0.065	0.178**	1				
Hg	0.048	0.018	−0.007	1			
Ni	0.389**	0.005	0.049	0.243**	1		
Pb	−0.018	0.247**	0.142*	−0.007	−0.04	1	
Zn	0.045	0.196**	0.250**	0.094	0.086	0.027	1

* and ** indicate the correlation is significant at the 95% and 99% confidence interval.

and afternoon by the workers at the monitoring stations. These data were analyzed and used as the fundamental dataset for this study, consisting of the monthly mean concentrations of As, Cr, Cu, Hg, Ni, Pb, and Zn from January 2020 to December 2022 for each sampling point.

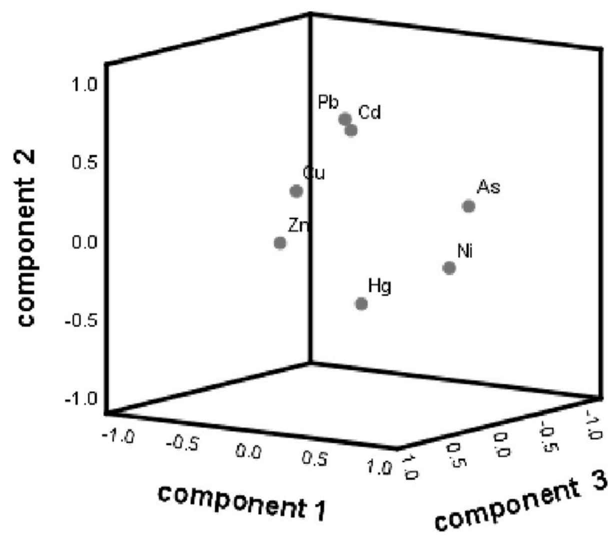

FIGURE 3
Principal components PC1, PC2 and PC3 showing three groups of heavy metals in Lake Taihu from 2020 to 2022.

TABLE 3 Statistical analysis of ecological risk of heavy metals in Taihu Lake from 2020 to 2022.

Sampling sites	Item	E_r^{As}	E_r^{Cd}	E_r^{Cu}	E_r^{Hg}	E_r^{Ni}	E_r^{Pb}	E_r^{Zn}	*RI*
Total	Mean	0.858	5.913	0.016	138.437	1.755	0.182	0.012	147.172
	Median	0.239	2.632	0.004	78.223	0.608	0.098	0.005	89.418
	Std. deviation	1.524	13.352	0.052	236.447	3.354	0.251	0.022	237.999
	Skewness	3.408	5.492	10.236	6.355	4.232	4.351	4.583	6.231
	Kurtosis	14.107	33.821	127.335	51.124	21.755	28.776	26.793	49.704
	Range	10.035	116.764	0.707	2324.502	24.891	2.414	0.191	2335.760
	Minimum	0.011	0.000	0.000	4.400	0.016	0.012	0.000	5.423
	Maximum	**10.046**	116.764	**0.707**	2328.902	**24.908**	**2.426**	**0.191**	2341.183
	5th percentile	0.026	0.639	0.001	12.017	0.057	0.021	0.001	14.300
	95th percentile	3.718	19.237	0.081	351.351	7.791	0.641	0.050	390.444
S1	Minimum	0.011	0.601	0.000	4.933	0.045	0.018	0.000	5.423
	Maximum	3.823	18.392	0.085	2328.902	14.796	0.917	0.063	2341.183
	Average	**0.559**	**2.152**	**0.009**	**218.436**	**2.628**	**0.165**	**0.007**	**223.955**
	Months of E_r^i≥30 or IR ≥ 70	0	0	0	28	0	0	0	23
S2	Minimum	0.028	0.512	0.001	32.552	0.063	0.049	0.001	38.215
	Maximum	9.658	64.225	0.090	341.332	14.700	0.313	0.033	368.795
	Average	0.907	4.962	0.008	95.859	1.282	0.101	0.007	103.127
	Months of E_r^i≥30 or IR ≥ 70	0	1	0	36	0	0	0	20
S3	Minimum	0.073	0.988	0.001	39.890	0.045	0.018	0.001	41.737
	Maximum	2.595	11.101	0.013	2171.778	6.438	0.772	0.044	2175.312
	average	1.235	2.381	0.004	180.953	1.671	0.156	0.009	186.408
	Months of E_r^i≥30 or IR ≥ 70	0	0	0	36	0	0	0	17
S4	Minimum	0.059	0.000	0.002	46.800	0.057	0.031	0.001	49.581
	Maximum	**10.046**	70.519	**0.707**	819.396	**24.908**	0.339	**0.191**	823.619
	Average	1.877	6.143	0.041	228.240	4.312	0.150	0.034	240.798
	Months of E_r^i≥30 or IR ≥ 70	0	1	0	36	0	0	0	32
S5	Minimum	0.022	0.492	0.000	4.400	0.016	0.012	0.000	5.423
	Maximum	3.717	20.807	0.090	230.123	3.190	0.538	0.060	234.703
	Average	0.391	4.955	0.011	76.468	0.579	0.176	0.007	82.587
	Months of sample with E_r^i≥30 or IR ≥ 70	0	0	0	30	0	0	0	17
S6	Minimum	0.012	0.412	0.000	9.649	0.073	0.013	0.000	10.467
	Maximum	1.927	6.525	0.015	156.179	4.707	0.141	0.051	167.020
	Average	0.257	2.315	0.003	50.395	1.165	0.060	0.008	54.204
	Percentage of E_r^i≥30 or IR ≥ 70	0	0	0	18	0	0	0	9
S7	Minimum	0.024	0.925	0.000	4.400	0.039	0.015	0.000	6.978
	Maximum	5.791	116.764	0.123	347.600	2.401	**2.426**	0.037	399.456
	Average	0.778	18.482	0.035	118.707	0.646	0.469	0.010	139.126
	Months of E_r^i≥30 or IR ≥ 70	0	8	0	28	0	0	0	24

TABLE 4 Analysis results of Mann-Kendall test.

Site	Z (E_r^{As})	Z (E_r^{Cd})	Z (E_r^{Cu})	Z (E_r^{Hg})	Z (E_r^{Ni})	Z (E_r^{pb})	Z (E_r^{zn})	Z (RI)
S1	−2.275[2)]	−3.174[3)]	−1.621[1)]	−4.427[3)]	−2.901[3)]	−1.662[2)]	−2.983[3)]	−4.617[3)]
S2	−0.913	−4.427[3)]	−2.016[2)]	−2.738[3)]	−4.209[3)]	−3.364[3)]	−3.610[3)]	−3.936[3)]
S3	−3.283[3)]	0.558	1.730[2)]	−0.749	−2.411[3)]	1.784[2)]	0.913	−0.831
S4	−3.051[3)]	−3.691[3)]	−0.395	−1.757[2)]	−3.065[3)]	−1.825[2)]	−1.784[2)]	−1.921[2)]
S5	0.9944	−0.831	−3.909[3)]	−1.921[2)]	−3.065[3)]	0.804	0.994	−1.812[2)]
S6	−3.119[3)]	−3.882[3)]	−4.372[3)]	−5.108[3)]	−2.520[3)]	−2.71[3)]	0.531	−4.863[3)]
S7	−2.629[3)]	−2.493[3)]	−1.240[1)]	−2.302[2)]	−3.909[3)]	−2.629[3)]	−0.123	−3.119[3)]

[1), 2)] and [3)] representing the values of Z passed the significance tests with confidence levels of 90%.

TABLE 5 The parameters of mean gravity cente and the standard-deviation from 2020 to 2022 (°).

Element	Mean gravity center		Standard-deviation ellipse				
	Range of longitude	Range of latitude	Center_X	Center_Y	XStdDist	YStdDist	Rotation
E_r^{As}	119.96389–120.55637	31.20288–31.40103	120.30247	31.30370	0.22115	0.05754	94.87887
E_r^{Cd}	120.07586–120.47155	31.19215–31.49836	120.21906	31.36165	0.09301	0.11511	24.36835
E_r^{Cu}	119.94877–120.48528	31.23077–31.49501	120.22648	31.38338	0.09961	0.15326	83.12754
E_r^{Hg}	120.08132–120.52759	31.25817–31.43108	120.26047	31.32805	0.13164	0.05425	97.99898
E_r^{Ni}	119.99246–120.53603	31.22342–31.43024	120.26256	31.34693	0.16160	0.06824	96.15280
E_r^{Pb}	120.12073–120.51680	31.24413–31.49590	120.25066	31.35937	0.11176	0.08249	107.25477
E_r^{Zn}	120.00013–120.38333	31.27289–31.40870	120.20977	31.33581	0.04070	0.15855	84.97133
RI	120.08413–120.51203	31.26005–31.43044	120.25813	31.33051	0.12426	0.05267	96.66797

2.3 Modified potential ecological risk index

Hakanson (1980) proposed the concept of potential ecological risk, where toxicity coefficients are determined using the elemental abundance and release capacity of sediment (Hakanson, 1980). The ecological risk can be calculated using the following formula.

$$RI = \sum_{i=1}^{n} E_r^i = T_i \times P_i = T_i \times C_m^i \Big/ C_s^i \tag{1}$$

Where the RI combines the E_r^i values for all of the heavy metals; E_r^i represents the potential ecological risk of each heavy metal; T_i corresponds to the toxic response coefficient, P_i represents the contamination factor of the heavy metal; C_m^i and C_s^i are the actual concentration and the background concentration or baseline value of each heavy metal respectively. In this study, the C_s^i values were based on the grade Ⅳ standard outlined in the Chinese environmental quality standards for surface water (GB 3838-2002), as specified in the “action plan for comprehensive treatment of water environment in Taihu Lake Basin during the 13th 5-year plan.”

The abundance and release of heavy metals in sediment impact the toxicity coefficient, as discussed in Hakanson’s (1980) study. Unlike sediment, the toxicity coefficient of heavy metals in water does not involve the release effect, we modified the toxicity coefficient and the classification criteria of RI and Ei based on previous research studies (Hakanson, 1980; Ma et al., 2020; Xu et al., 2008). The specific formula is as following.

$$T_i = R\left(\sqrt{A_i / A_{\min}}\right) \tag{2}$$

Where R refers to the response to the regularization treatment, Amin represents the minimum abundance of heavy metals in this study; Ai denotes the abundance of heavy metals. The optimized toxicity coefficients for As, Cd, Cu, Hg, Ni, Pb, and Zn were determined to be 11, 16, 2, 33, 3, 3, and 1, respectively. Additionally, the updated classification criteria were derived and are presented in Table 1 (Hakanson, 1980; Abu El-Magd et al., 2021; Lécrivain et al., 2018; Suresh et al., 2012).

2.4 Spatial-temporal dynamics analysis

2.4.1 Mann-Kendall test

The Mann-Kendall test was employed to assess the significance of the temporal trend regarding the potential ecological risk posed by heavy metals in Taihu Lake from 2020 to 2022. The Mann-Kendall test is defined by the following equations.

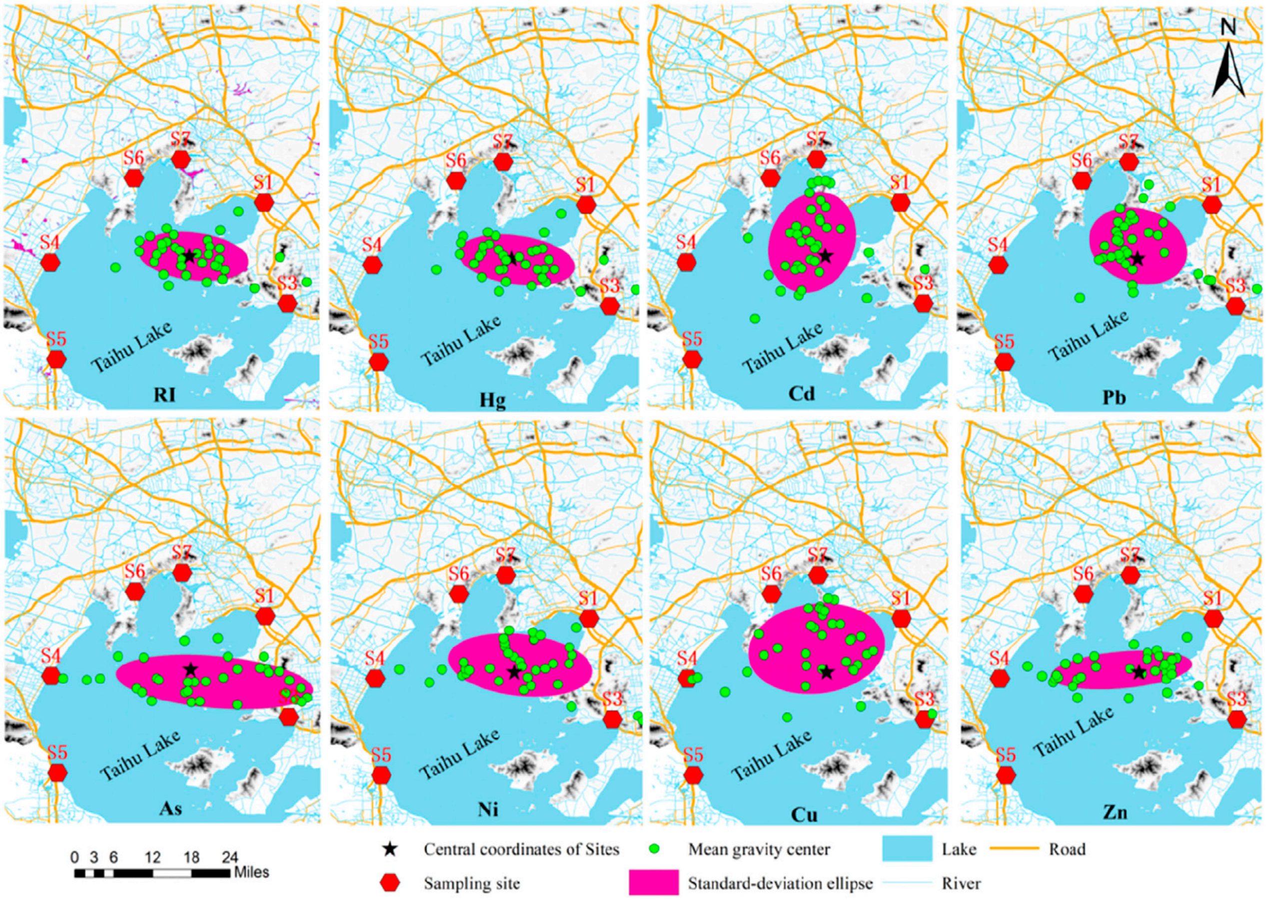

FIGURE 4
Analysis of weighted average gravity center and standard deviation ellipse about the ecological risk of aquatic heavy metals.

$$S = \sum_{k=2}^{n} \sum_{j=1}^{k-1} sign\left(x_k - x_j\right) \tag{3}$$

$$sign = \begin{cases} 1 & \left(x_k > x_j\right) \\ 0 & \left(x_k = x_j\right) \\ -1 & \left(x_k < x_j\right) \end{cases} \tag{4}$$

$$Z = \begin{cases} (S-1)/\sqrt{n(n-1)(2n+5)/18} & (S>0) \\ 0 & (S=0) \\ (S+1)/\sqrt{n(n-1)(2n+5)/18} & (S<0) \end{cases} \tag{5}$$

The variables x_k and x_j represent the $E_r^{\,i}$ or RI in the kth and jth month of each sampling. The significance of the temporal trend of $E_r^{\,i}$ or RI in the sampling site is determined by the absolute value of Z. When Z is greater than or equal to 1.28, 1.64, and 2.32, the trend passes the significance test with reliability levels of 90%, 95%, and 99%, respectively (Yuan et al., 2020; Gocic and Trajkovic, 2013).

2.4.2 Mean gravity center and standard-deviation ellipse

The temporal changes of the RI between 2020 and 2022 were analyzed by calculating the mean gravity center. This mean gravity center was computed using the following relationship.

$$\left.\begin{aligned} x_m &= \sum_{j=1}^{n} P_{RI\,j} \times x_j \Big/ \sum_{j=1}^{n} P_{RI\,j} \\ y_m &= \sum_{j=1}^{n} P_{RI\,j} \times y_j \Big/ \sum_{j=1}^{n} P_{RI\,j} \end{aligned}\right\} \tag{6}$$

Where n represents the number of surveying points; P_{RIj} is the monthly percentage of RI for heavy metals in the water environment at a specific site; x_j and y_j correspond to the longitude and latitude, respectively; the (x_m, y_m) represents the mean gravity center. In order to clarify the directional distribution of the mean gravity center, we adopted the standard deviation ellipse, which was described in the previous studies (Cao et al., 2021; Gong, 2002).

2.5 Statistical analysis

In this study, IBM SPSS Statistics 25.0 software (IBM, Armonk, NY, United States) was utilized to analyze the correlation analysis, principal component analysis of heavy metals. We employed correlation analysis to identify any significant associations between the heavy metals. Additionally, we performed principal component analysis to elucidate the original variations using fewer new and independent variables. Through a combination of correlation analysis and principal component analysis, we were able to identify possible sources of metals (Li Y. et al., 2020; Zhang P. et al., 2018). Furthermore, we utilized ArcGIS 10.3 to analyze the sampling sites map, mean gravity center, and standard deviation ellipse.

3 Results and discussion

3.1 Overall characteristics of heavy metals in Taihu lake

The concentrations of heavy metals were analyzed monthly from 2020 to 2022, and the results are summarized in Supplementary Table S1. The maximum concentrations of As, Cu, Pb, and Zn were 0.0913, 0.3536, 0.0404, and 0.3816 mg L^{-1}, respectively. All of these concentrations were below the referenced standard values of 0.1, 1.0, 0.05, and 1.0 mg L^{-1}. However, the mean concentration of Hg was relatively high at 0.0031 mg L^{-1}, which is three times higher than the corresponding national standard. In contrast, the mean concentrations of the other elements were lower than their respective standards. Considering the cumulative effect of ecological risk associated with heavy metals (Zhang et al., 2019), it is necessary to analyze all of the heavy metals using the potential ecological risk index.

The coefficient of variation revealed that the high level of spatial-temporal variation for the seven heavy metals exceeded 1 during the monitoring period. Additionally, the skewness values were higher than 3, indicating that most of the monthly concentrations of heavy metals were less than the mean concentration. The kurtosis values ranged from 14.1070 to 127.3560, suggesting the presence of a certain number of extreme values of heavy metal concentrations at the seven sampling sites (Zhang P. et al., 2018). The analysis of box plots for the metal concentrations, including parameters, medians, outliers, and the 25th and 75th percentiles, was conducted (Figure 2). The outliers further verified that there were relatively large changes in heavy metal concentrations from 2020 to 2022, which may be attributed to the governance efforts in the Taihu Lake Basin (Zhu, 2017). Furthermore, aquatic heavy metals can originate from both external sources and sediment release (Zhao et al., 2020). Therefore, it is important to further investigate the sources and ecological risks of heavy metals from a spatial-temporal perspective.

3.2 Source identification

3.2.1 Correlation analysis

Table 2 presents the results of the correlation analysis. The pairs As-Ni, Cd-Cu, Cd-Pb, Cd-Zn, Cu-Zn, and Hg-Ni showed significant positive correlations ($P < 0.01$) with coefficients of 0.389, 0.178, 0.247, 0.196, 0.250, and 0.243, respectively, indicating the possibility of shared sources (Zhao et al., 2020). Moreover, the As-Cd and Cu-Pb pairs exhibited significant positive relationships at the 0.05 level, with correlation coefficients of 0.162 and 0.142, respectively. Although these positive correlations were relatively low, they were statistically significant ($P < 0.05$) and suggested a potential common origin (Chai et al., 2021). All significant correlation coefficients were less than 0.4, indicating a relatively weak correlation. In contrast, other pairs of heavy metals such as As-Cu, As-Hg, As-Pb, Cd-Hg, Cd-Ni, Cu-Hg, and Cu-Ni did not show significant correlations ($P < 0.05$ or $P < 0.01$), implying that they likely originated from different sources (Zhang Z. et al., 2018).

3.2.2 Principal component analysis

As mentioned earlier, the study employed principal component analysis (PCA) to further investigate the relationships among the heavy metals from 2020 to 2022. The Kaiser-Meyer-Olkin value was 0.529, and Bartlett's test of sphericity was highly significant ($p < 0.001$), indicating the suitability of PCA for this study. The rotation method used was the Kaiser Normal Maximum Variance method, which converged after five iterations. The results are presented in Figure 3 and Supplementary Table S2. Based on these results, three principal components were extracted, which accounted for the majority of the original information, with a cumulative contribution rate of approximately 58.003%. The first principal component had high positive loadings for As, Hg, and Ni, contributing 20.933% of the total variance. The second principal component, dominated by Cd and Pb, explained 18.706% of the total variance. The third principal component, with a contribution rate of 18.364%, was characterized by Cu, Hg, and Zn.

3.2.3 Analysis of the source of the heavy metals

According to the correlation analysis and principal component analysis the heavy metals in Taihu Lake from 2020 to 2022, the loading of As and Ni on principal component 1 were respectively 0.808 and 0.81. Factors such as metal smelting, manufacturing, paper-making, and printing and dyeing might contribute to the presence of As and Ni in the water environment. Hg had a loading of 0.350 and showed a significant positive correlation with Ni, indicating that industrial enterprises could be a source of As, Hg, and Ni (Niu et al., 2020; Vu et al., 2017). Moreover, the cities surrounding Taihu Lake are key areas for economic development in China, with more than 3,000 large-scale enterprises involved in paper-making, printing and dyeing, non-ferrous smelting, and metal manufacturing in 2020, according to the Statistical Yearbook 2020 of Suzhou and Wuxi. Therefore, the manufacturing industry, including activities such as non-ferrous melting, metal fabrication, paper-making, and textile production, was inferred as the probable source of principal component 1, which may involve the burning of fossil fuels.

The loading of Cd, Pb, and Cu were 0.694, 0.340, and 0.711, respectively, and the relationships between Cd-Cu, Cd-Pb, and Cu-Pb were significantly positive. The Pearl River Delta, Yangtze River Delta, and Bohai Rim regions are prominent hubs for the manufacturing and processing of electronic products in China, and cities surrounding Taihu Lake hold a pivotal position within the Yangtze River Delta (Fu, 2011). Moreover, electroplating plays a critical role in electronic manufacturing, often resulting in the discharge of wastewater, gas, and residue containing the heavy metals Cd, Pb, and Cu (Bian et al., 2017; Guo et al., 2015). Therefore, the sources of principal component 2 was dominated by electronic manufacturing. Consequently, the dominant sources of principal component 2 can be attributed to electronic manufacturing.

Principal Component 3 predominantly comprised Cu, Hg, and Zn, with loadings of 0.600, 0.417, and 0.815, respectively. The area surrounding Taihu Lake is critical for grain production in China, experiencing extensive use of fertilizers and pesticides. This practice can result in the potential introduction of Cd, Hg, and Zn into the soil, subsequently leading to the transmission of these heavy metals into Taihu Lake through surface runoff (Li Y. et al., 2020; Zhang et al., 2019; Zhou et al., 2020). Statistical data reveals that the average fertilizer consumption in Suzhou and Wuxi exceeded 124 kilotons, while pesticide usage was larger than 6 kilotons in 2020. As a result, Principal Component 3 is characterized as originating from agricultural sources.

Overall, the heavy metal concentrations at the sampling sites in Taihu Lake were primarily attributed to industrial and agricultural activities during the monitoring period. It is worth noting that certain months exhibited elevated levels of heavy metals, which can also be attributed to these contributing factors. To address this issue, it is crucial to strengthen management practices in the future.

3.3 Potential ecological risk index

The potential ecological risk of heavy metals in different months and sampling sites was assessed by Equations 1, 2, and presented in Supplementary Table S3. Descriptive statistics were analyzed and shown in Table 3. The results showed that the maximum and 95th percentile of the *RI* were 2341.183 and 390.444, significantly surpassing the threshold value of 280. The mean and median *RI* values were 147.172 and 89.418, slightly higher than 140 and 70, respectively. These findings collectively indicated the presence of substantial potential ecological risk in certain months of Taihu Lake between 2020 and 2022.

Specifically, regarding the potential ecological risk of different heavy metals, the maximum values of potential ecological risk for As Cu, Ni, Pb, and Zn were 10.046, 0.707, 24.908, 2.426, and 0.191, respectively. These maximum values were observed at the sampling sites S4 or S7. The maximum, mean, and 95th percentile of E_r^{Cd} were 116.764, 5.913, and 19.237, respectively. This indicates that the ecological risk of Cd needs attention, particularly at S7, where the E_r^{Cd} exceeded 30 with the time of 8 months. In terms of the potential ecological risk associated with Hg, the maximum, mean, and median values of the E_r^{Hg} were 2328.902, 138.437, and 78.223, respectively. These values were significantly higher than those of the other heavy metals. Moreover, the month of $E_r^{Hg\ in}$ sampling sites exceeded 30 were 18 at least. Additionally, the kurtosis and skewness of the E_r^{Hg} were calculated to be 51.124 and 6.355, respectively. The corresponding standard errors were 0.306 and 0.153, indicating that the distribution of the E_r^{Hg} exhibited right-skewness and asymmetry. Therefore, it is without a doubt that Cd and Hg in the Taihu Lake should be considered as priority factors of ecological risk.

In terms of the potential ecological risk at different sampling sites, it was observed that the month which the E_r^{Hg} exceeding 30, was emerging in the 7 sampling sites during the monitoring period. And the amount of the month was 28, 36, 36, 36, 30, 18, and 28 at S1, S2, S3, S4, S4, S5, S6, and S7, respectively. Additionally, the E_r^{Cd} exceeded 30 in sampling sites S2, S3, and S7 with the month 1, 1, and 8 months, respectively. Notably, the *RI* higher than 70 appearing in the 7 sampling site, and the contribution rate of E_r^{Hg} were more than 90% in the different sampling sites, except the S7 with 85.32% (Figure 3). This further reinforces the idea that Hg and Cd were the primary factors contributing to the ecological risk in Taihu Lake. These findings align with previous studies on Taihu Lake sediments (Li Y. et al., 2020; Zhang et al., 2019; Niu et al., 2020; Yu et al., 2017), emphasizing the need to consider sediment and water management in controlling the ecological risk associated with heavy metals in Taihu Lake.

The maximum values of the *RI*, E_r^{Cd} and E_r^{Hg} surpassed the minimum threshold for high or very high potential ecological risk, respectively. Conversely, the minimum value among them was significantly lower than the maximum value for the low ecological risk level. Moreover, all of the sampling sites exhibited the aforementioned characteristics, except for the E_r^{Hg} in S2, S3, and S4. Hence, a comprehensive analysis of the temporal and spatial characteristics of ecological risk from heavy metals in Taihu Lake during the period from 2020 to 2022 is necessary.

3.4 Temporal variations analysis of risk

To examine the temporal variation characteristics of the ecological risk posed by heavy metals in Taihu Lake, we performed the Mann-Kendall test to quantitatively analyze the *RI* and E_r^i of the sampling sites from 2020 to 2022 (Equations 3, 4 and 5). The results are displayed in Table 4. We observed a decreasing trend in the *RI* and E_i^r values for sampling sites S1, S2, S4, and S7, which were statistically significant at a 90% confidence interval, except for E_r^{As} at S2, E_r^{Cu} at S4, and E_r^{Zn} at S7. The corresponding *Z*-scores were −4.862,659(E_r^{As}), −3.119,185(E_r^{Cd}), −3.881,955(E_r^{Cu}), −4.372,307(E_r^{Hg}), −5.107,835(E_r^{Ni}), and −2.519,865(E_r^{Pb}) at S6 respectively, These values indicate that the potential ecological risk has significantly decreased (Yuan et al., 2020). At S3, we found a significant increasing trend in E_r^{Cu} and E_r^{Pb}, while E_r^{As} and E_r^{Ni} exhibited a significant decreasing trend. Additionally, the decreasing trends of E_r^{Cd}, E_r^{Cu}, and E_r^{Hg} were statistically significant at a 95% confidence level, while the increasing trends in E_r^{As}, E_r^{Pb}, and E_r^{Zn} were not statistically significant at S5 (Gocic and Trajkovic, 2013; Frazier et al., 2018).

Although there were significant increasing trends of E_r^{Pb} and E_r^{Cu}, and non-significant increasing trends of E_r^{As}, E_r^{Cd}, E_r^{Hg}, and E_r^{Ni} at certain sampling sites, the dominant temporal variation characteristic of E_r^i for heavy metals in Taihu Lake was a significant decreasing trend. Furthermore, the temporal trends of *RI* showed significant decreases, with significant values of *Z(RI)* passing the 99% confidence interval test at S1, S2, S6, and S7, and the 95% confidence interval test at S4 and S5. This phenomenon may be attributed to a series of measures implemented to prevent and control environmental pollution around Taihu Lake, such as the closure of heavy polluting enterprises in printing and dyeing, electroplating, and paper-making (Zhu, 2017), the establishment of large-scale circular (organic) agricultural projects (Xu et al., 2018), and the implementation of wetland protection and recovery projects (Jiang et al., 2017). Additionally, future targeted measures should be taken to reduce the ecological risk of Cd and Hg based on the results of the source and potential ecological risk assessment in Taihu Lake from 2020 to 2022. To obtain a spatial perspective for risk control, we further conducted an analysis of the temporal characteristics of the sampling sites in Taihu Lake between 2020 and 2022. This analysis allowed us to further examine the spatial distribution characteristics of the sampling sites, providing valuable reference for risk control.

3.5 Spatial distribution characteristics of risk

The spatial variation characteristics of the E_r^i and RI were analyzed of ecological risk caused by heavy metals in Taihu Lake from 2020 to December 2022 (Equation 6). The mean gravity centers of E_r^i and RI were found to be concentrated within the geographical coordinates of 120.55637–119.94878 N and 31.49836–31.19215 E, as determined through the analysis of spatial characteristics (Table 5). The major axis of the standard-deviation ellipse indicates the direction, while the minor axis represents the magnitude of dispersion (Peng et al., 2016). Therefore, the concentration degree of the mean gravity centers of the E_r^i and RI was increasing according to the E_r^{Cu}, E_r^{As}, E_r^{Ni}, E_r^{Cd}, E_r^{Pb}, E_r^{Hg}, RI, and E_r^{Zn}. Moreover, a significant proportion of the mean gravity centers was found in the northeastern region of Taihu Lake from 2020 to 2022. The spatial aggregation patterns of ecological risk associated with heavy metals need to be further analyzed due to the spatial heterogeneity present in different sampling sites.

Therefore, the standard deviation ellipses of the mean gravity centers of ecological risk were analyzed using ArcGIS 10.3, and the results are presented in Table 5 and Figure 4. The results indicate that the center coordinates of the standard deviation ellipse of the E_r^{Ni}, E_r^{Pb}, E_r^{Hg}, and RI were in the northeast of the central site, while the E_r^{As} was in the southeast, and the E_r^{Cu}, E_r^{Cd}, and E_r^{Zn} were in the northwest. This suggests that the northeastern part around Taihu Lake played a more significant role in terms of ecological risk from 2020 to 2022 (Shi et al., 2018). These findings are consistent with the results of previous studies (Xia et al., 2012; Ohore et al., 2019; Wu et al., 2019).

The pollutants in the basin indirectly indicate the pollution level of lake due to the river acting as a conduit between the lake and the basin. The pollutants entering the lake through the river have a significant impact on the overall water quality of Taihu Lake, particularly considering its numerous water networks, dense population, and substantial industrial activities (Li B. et al., 2020; Cotte and Vennemann, 2020; He et al., 2020). Consequently, heavy-metal pollutants from the basin, even those located far from Taihu Lake, can enter the lake through the river network, resulting in water pollution. According to the aforementioned analysis, Hg, which predominantly stems from industrial activities and poses a primary ecological risk, is primarily influenced by the northeastern part of Taihu Lake. However, despite the relocation of pollution-intensive enterprises surrounding Taihu Lake to suburban areas or farther away from the lake in recent years as a result of Taihu's water pollution prevention and control regulations (Yuan et al., 2019), these enterprises cannot be disregarded in water pollution management due to the extensive water network of Taihu Lake (Niu et al., 2020; Zhang S. et al., 2018). Hence, in order to minimize the ecological risk of Taihu Lake, the stricter regulations and enforcement should be implemented to regulate pollutant discharge, particularly in the northeastern part of the lake, with special attention given to the pollution-intensive enterprises located around the river network. Moreover, comprehensive efforts are required to prevent pollutants from entering the lake within the Taihu basin, while simultaneously enhancing the treatment methods for heavy metal pollution from industrial operations and efficiently reducing and eliminating outdated production capacity (Bian et al., 2017; Zhang et al., 2019; Xia et al., 2012; Fu, 2011).

4 Conclusion

Based on a continuous investigation conducted from 2020 to 2022 of heavy metals in Taihu Lake, this study analyzes the sources apportionment, spatiotemporal variation characteristics of ecological risk of heavy metals in Taihu Lake though the modified potential ecological risk model, principal component analysis, Mann-Kendall test, mean gravity center and standard-deviation ellipse. Firstly, compared to the referenced standard, Cd, Hg, and Ni were found to exceed that standard. These heavy metals predominantly originated from industrial production and agricultural activities, including non-ferrous melting, metal fabrication, paper-making, textile production, electronic manufacturing, and the use of fertilizers and pesticides. Secondly, the assessment of E_r^i and RI highlighted that Cd and Hg primary factors of ecological risk according to the modified potential ecological risk model. Special attention should be given to Hg, as the average E_r^{Hg} value was 218.436. Thirdly, the overall ecological risk of heavy metals significantly decreased, as indicated by the absolute values of Z (E_r^i) and Z (RI) in most sites being higher than 1.64. These results indicate that a series of environmental control measures have achieved progress in mitigating the impact of heavy metals in Taihu Lake—suggesting that these measures should continue to be implemented. Finally, the northeastern part of Taihu Lake plays a critical role in causing the ecological risk of heavy metals. Therefore, the management and control of the ecological risk associated with heavy metals should primarily focus on the northern part of Taihu Lake, particularly with regards to Hg and Cd. This study provides valuable and in-depth insights for the ecological risk management of heavy metals in Taihu Lake and contributes to the research perspective and foundational theory of ecological risk associated with heavy metals in the water environment.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding authors.

Author contributions

GB: Conceptualization, Writing – original draft, Writing – review and editing. CJ: Writing – original draft, Writing – review and editing. DH: Conceptualization, Software, Writing – review and editing, Writing – original draft. YH: Data curation, Investigation, Supervision, Writing – review and editing. YL: Formal Analysis, Methodology, Writing – review and editing. DL: Conceptualization, Methodology, Resources, Writing – review and editing. XF: Methodology, Supervision, Writing – original draft, Writing – review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The author(s) declare that Generative AI was used in the creation of this manuscript. All generated content has been carefully reviewed and verified by the authors, who take(s) full responsibility for the final content.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2025.1604407/full#supplementary-material

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