Optimal Interpolation and Ecological Risk Assessment of Spatial Distribution of Heavy Metals in Soil Based on GIS and Geostatistics – A Case Study of Low-lying Land of the Lower Yellow River, China

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Abstract

Soil environmental quality plays an important role in ensuring human health and food security. Therefore, increasingly attention has been paid to the ecological and environmental problems affecting river basins worldwide. The Yellow River is the second longest river in China and the fifth longest river in the world, thus it has great significance globally and locally. In recent years, the ecological protection and exploitation of the Yellow River Basin have attracted much attention, especially regarding changes in vegetation, water, and sediment, as well as soil quality problems. This research concentrates on the assessment of soil heavy metals in the low-lying land, a typical landform unique to the Yellow River Basin, which is of great significance for the study of food security, cultivated land protection, and cultivated land resources in developing countries. Here, 156 surface soil (0-20 cm) samples, and eight elements (Cd, Cr, Ni, Pb, Cu, Zn, As, and Hg) were collected to be measured and studied. We found that only the average value of Cd exceeded the standard. By comparing the above six interpolation methods, the optimal interpolation model was selected for the analysis of the spatial distribution characteristics of the heavy metal content in eight soils in the study area. Regarding the spatial distribution, we observed that higher concentrations in the west, with lower concentrations in the east; all heavy metals exhibited high-value zones. The evaluation of the potential ecological risk index revealed that only Cd reached the moderate level. Zn, Pb, Cd, and Hg were greatly affected by anthropogenic sources, and Cu, Cr,

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Ni, and As were greatly affected by natural sources. Therefore, Cd was found to be the main risk factor in the region and Cd soil levels should thus be closely monitored in the study area.

Keywords: heavy metals, interpolation method, spatial analysis, pollution assessment, low-lying land

Introduction

Soil is an important natural resource and an important part of human development and the ecological environment [1-3]. Urbanization continues to accelerate with socioeconomic development, consequently, the soil environment is also facing serious threats [4-5]. In the past 50 years, a good deal of heavy metals had been discharged into the global environment. Notably, most of these heavy metals have entered the soil, causing soil heavy metal pollution [6-7]. Heavy metals are hard to degrade, easy to accumulate, and highly toxic. Moreover, they can not only threaten soil quality, reduce crop yields, and lead to harvest failure, but also through the food chain to enter the human body, compromising human health [8-10]. Therefore, research on soil heavy metal pollution has received widespread attention [11-12]. According to a research report by the Ministry of Agriculture of China, which reduces its output by approximately 1.0×10^{10} kg, leading to a total loss of more than 20 billion yuan [13-14]. Some scholars have made promising findings on soil heavy metal assessment [15-17], including different scales [18-19], and different sources [20-21]. These results have important role and theoretical significance for protecting the quality of farmland soil environments and sustainable development.

Some methods for the study of heavy metal pollution have been developed and discussed in previous studies [22-24]. In terms of evaluation of soil heavy metal pollution, such as geo-accumulation index [25], Nemerow comprehensive pollution index [26] and ecological risk assessment index [27]. These methods play an important role in the assessment of soil heavy metal pollution. Spatial analysis methods can determine the distribution characteristics of heavy metals in soil, such as kriging interpolation methods [28], and inverse distance weighted interpolation [29]. In addition, Multivariate statistical analysis can be used to identify the sources of soil heavy metal pollution [30-31]. Therefore, it is effective to combine above methods to study soil heavy metals. Moreover, worldwide research on low-lying land ecosystems has mainly focused on protection and comprehensive utilization [32-34]. There are few studies on soil heavy metal pollution in low-lying land.

The Yellow River has a wide drainage area in China, and is therefore an important ecological barrier and a relevant economic zone in China [35]. Research on heavy metals in the upper reaches of the Yellow River Basin has focused on the Baotou City section [36], the source area [37], and the Lanzhou City section [38]. Research on soil heavy metals in the lower Yellow River has focused on the beach of the Lower Yellow River and the Yellow River Delta areas [39-40]. Because the Yellow River flows through the Loess Plateau in the middle reaches, carrying a large amount of sediment and silting and settling in the lower Yellow River, the river channel in the lower reaches of the Yellow River changes from deep to shallow, from narrow to wide. During the flood period, it is easy to have a breach. The strong erosion of the ground near the breach and the continuous accumulation of the river bank form different types of micro-geomorphology, such as erosion depression, sand land, sand dune and sand ridge [41]. Influenced by the "suspended river" in the lower Yellow River, low-lying land has been formed after many floods in Kaifeng, China. The low-lying land of the lower Yellow River is the area where the Yellow River due to the formation of an above-ground river, where the groundwater leaks to the side. This area is prone to soil salinity and waterlogging, serious sandy soils, and unreliable crops. However, this area is an open ecosystem, after decades of continuous transformation by human. And the low-lying land of the lower Yellow River is already the core area for grain production and the development of production capacity. This region is a cultivated land reserve in Henan Province, China, and it plays an important role in increasing the area of cultivated land and increasing grain output. Due to the unique micro-geomorphology form of low-lying land, affected by the double effects of the Yellow River and human activities. With the economic development and population growth, the increasing demand for food, a large number of chemical fertilizers and pesticides are used, and the soil environment of low-lying land is polluted to a certain extent. However, research on soil environmental quality in the low-lying land of the lower Yellow River remains scarce. Whether the soil environment of low-lying land is polluted and damaged, and the degree of pollution, there are no specific data and literature to reference.

Therefore, this study sought to study the low-lying land of the Lower Yellow River depression and analyze the heavy metal contents of farmland soils that it can provide a technical support for local agricultural development and contribute to the protection of cultivated land resources. Additionally, characterizing soil heavy metal content in the aforementioned low-lying land provides a reference for soil environmental quality assessment of other low-lying land environments to facilitate the protection of watershed soil quality and food security in these ecosystems. It is helpful to judge the impact of human activities on the soil environment of low-lying land, and has some practical value. And it

also has reference value and significance for the study of low-lying land in other regions of the world.

Materials and Methods

Study Area

The low-lying land area of the lower Yellow River is located on the southern bank of the Yellow River levee (Fig. 1). Its width ranges from approximately 1 km to 23 km, it spans 95 km from west to east, and covers a total area of approximately 1,327.86 km². Its land-use types are mainly agricultural, urban, and transportation, among others. The primary crops in the region are wheat, corn, peanuts, rice, and vegetables. The terrain in the study area is generally flat and low. The region exhibits a temperate continental monsoon climate, four distinct seasons, droughts in spring and autumn, more rain in summer, and less snow in winter. The annual average precipitation and temperature is 634.3 mm and 14ºC. The low-lying land area of the Kaifeng (Henan Province, China) section of the lower Yellow River has the advantages of being a good arable land foundation and thus having great potential for agricultural production. We utilized ecological risk assessment to confirm the risk status of soil heavy metals in the Low-lying land. This procedure has positive significance for ensuring food safety in Henan Province, consolidating the agricultural status of Henan Province, facilitating rapid agricultural development in Henan Province, China, and promoting food production.

Sampling and Laboratory Analysis

Soil samples were according to a regular 3 × 3 km grid to collect. We collected 156 surface soil samples (0-20 cm) distributed throughout the low-lying land according to the diagonal method (Fig. 1). Each sample point was divided into four corner vertices and one center point for a total of 5 points. The samples from the 5 points were evenly mixed inside a plastic cloth to remove weeds, as well as gravel and other impurities. Afterward, 1 kg of the mixed soil was recovered following the quarter method, transferred to a sample bag, and brought to the laboratory. They were then allowed to ventilate and dry at room temperature. Larger pieces of gravel were crushed to ensure that they would pass a 0.84 mm nylon sieve. The sample was then divided into two parts via the quarter method, of which one part was stored, and the other part need get though a 0.15 mm nylon sieve that they were ground 20 g .

According to China's technical specifications for soil environmental monitoring, we performed the experimental determination of the eight elements in the study area. We utilized inductively coupled plasma mass spectrometry to measure the concentrations of Pb, Ni, Cd, Zn, Cu and Cr, whereas utilized atomic fluorescence spectrophotometry to measure As and Hg concentrations [42]. Our experiment eagents were all deemed safe and reliable. For quality control, we used national standard soil samples (GSS-2).
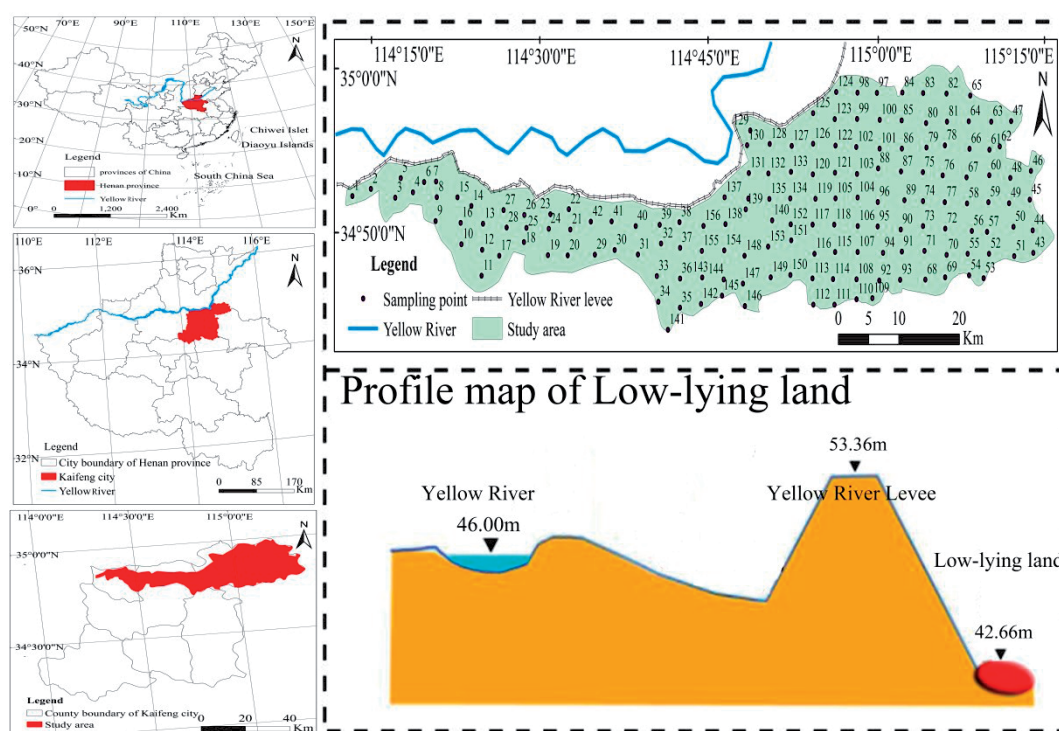

Fig. 1. Profiles and sampling points of the study area.

Table 1. The specific situation of Nemerow pollution index.

Class	Nemerow pollution index	Pollution Level
1	$P_c \leq 0.7$	Safety
2	$0.7 < P_c \leq 1$	Precaution
3	$1 < P_c \leq 2$	Slightly polluted
4	$2 < P_c \leq 3$	Moderately polluted
5	$P_c > 3$	Seriously polluted

Methods

Nemerow Comprehensive Pollution Index

A single factor index method is the most basic and widely used method to evaluate the pollution degree of a pollutant in soil on the basis of soil environmental quality standard. And its objective is clear and easy to calculate, but it can only evaluate the single element of heavy metal in the soil, which can not reflect the comprehensive situation of soil pollution [43]. The Nemerow comprehensive pollution index method is considering not only the maximum value of the pollutants, but also the average value of the pollutants, the pollution status of heavy metals in the soil can be more objectively evaluated [44-45]. The calculation formula is:

$$P_i = \frac{C_i}{S_i} \tag{1}$$

$$P_C = \frac{\sqrt{\left(\frac{1}{n}\sum_{i=1}^{n} P_i\right)^2 + P_{i\max}^2}}{2} \tag{2}$$

...where P_i is the single item element i pollution index, C_i is the actual value for element i, S_i is the standard value of fluvo-aquic soil i in Henan Province, P_c is the comprehensive item heavy metal, and P_{imax} is the maximum value of the single item of element i.

The single factor pollution index classification standard is the following [46]: $P_i \leq 1$, not polluted; $1 < P_i \leq 2$, slightly polluted; $2 < P_i \leq 3$, moderately polluted; $3 < P_i$, heavily polluted. The Nemerow pollution index classification standard has five domains [26], as shown in Table 1.

Ecological Risk Assessment

Potential ecological risk index method was proposed by Swedish geochemist Hakanson to evaluate the potential risk of heavy metals in sediments [47]. This model does not only consider the role and impact of heavy metals but also combines toxicological evaluation indicators, which is suitable for the evaluation of soil heavy metals in large areas [48-49]. It can be calculated as:

$$RI = \sum_{i=1}^{m} E_r^i = \sum_{i=1}^{m} T_r^i \times C_n^i = \sum_{i=1}^{m} T_r^i \times \frac{c_j^i}{c_r^i} \tag{3}$$

$$E_r^i = T_r^i \times C_n^i \tag{4}$$

$$C_n^i = \frac{c_j^i}{c_r^i} \tag{5}$$

...where E_r^i is the individual potential ecological risk index of element i; T_r^i is the toxicity coefficient of element i [50] (Table 2); C_n^i is the pollution coefficient of element i; c_j^i represents the actual values of element i; c_r^i is the reference value of element i in fluvo-aquic soil in Henan Province; RI is the comprehensive index.

We based on the sum of the maximum toxicity coefficient and the toxic response coefficient to assessment standard of the potential ecological risk The different types and quantities of pollutants involved in the assessment will result in different value, the more elements involved, the stronger the toxicity and the greater the RI value [51]. This study was graded according to Hakanson's (1980) grading criteria, shown in Table 3.

Deterministic Interpolation and Geostatistical Kriging Interpolation

Spatial interpolation refers to the process of estimating the value of other points using the values of known points. In geographic information system (GIS), it is mainly used to estimate the value of each pixel in the grid. Therefore, spatial interpolation is to convert point data into surface data. A method that can be used for spatial analysis and modeling. The types of spatial interpolation generally include deterministic interpolation and geostatistical Kriging interpolation. Deterministic interpolation is based on studying internal similarities, or on the basis of smoothness, using known point values as the basis to create a surface. Deterministic interpolation is mainly divided into two types: global interpolation and local interpolation. Among them, global interpolation mainly includes global polynomial interpolation (GPI); local interpolation mainly includes inverse distance weighted interpolation (IDW), radial basis function interpolation

Table 2. Toxicity response coefficients.

Elements	Pb	Cd	Zn	As	Hg	Cu	Ni	Cr
Coefficient of toxicity	5	30	1	10	40	5	5	2

Table 3. Potential ecological risk classification criteria employed in this study.

E_r^i	RI	Pollution Level
<40	<110	Low potential risk
40~80	110~220	Moderate potential risk
80~160	220~440	Strong potential risk
160~320	440~880	Very strong potential risk
>320	>880	Extremely strong potential risk

(RBF) and local polynomial interpolation (LPI). Kriging method is based on spatial autocorrelation, using the original data and the structure of the semi-variance function, the unbiased interpolation method of unknown sampling points of regional variation is the main method in geostatistics. When estimating the value of unknown samples, it can comprehensively consider the data of known points, data of nearby points, spatial location and distance, etc. Compared with other methods, it is more accurate and more realistic. Under different research areas, research conditions and research purposes, Kriging interpolation method has developed a variety of methods to meet research needs. The main Kriging methods involved in this article are: Ordinary Kriging interpolation method (OK), Universal Kriging interpolation method (UK), and Disjunctive Kriging interpolation method (DK). By comparing the above six interpolation methods, the optimal interpolation model was selected for the analysis of the spatial distribution characteristics of the heavy metal content in eight soils in the study area. Inverse distance weighted interpolation (IDW) can comprehensively reflect extreme value information and spatial distribution of element content in great detail [52-53]. This method is depended on the first law of geography, whereby two objects that are close to each other are more likely to share similar properties. In this study, utilizing the IDW to study the spatial distribution of single factor index method, Nemerow comprehensive pollution index and Potential ecological risk index method.

Multivariate Statistical Analysis

Currently, most studies on soil heavy metal sources use multivariate statistical analysis methods [54-55]. Therefore, this study used correlation analysis and principal component analysis in conjunction with the SPSS 20.0 software (https://www.ibm.com/products/spss-statistics) to distinguish the sources of soil heavy metal pollution and offer a theoretical foundation for soil heavy metal pollution control.

Results and Discussion

Descriptive Statistical Analysis and Content Analysis

In this study, using the SPSS 20.0 software to perform descriptive statistical research on soil heavy metal content data from 156 sampling points in this study area, and Kolmogorov-Smirnov method was used to test the normal distribution of heavy metals in soil (Table 4).

Table 4. Concentration statistics of heavy metals.

Heavy metal	Min. (mg/kg)	Average (mg/kg)	Max. (mg·/kg)	Standard deviation	Variance	K-S test	CV (%)	Skewness	Kurtosis	Background value*	Percentage overthe standard rate (%)
Cu	8.000	17.122	64.000	6.103	37.248	Lognormal distribution	35.600	3.454	22.094	24.100	10.260
Cr	22.200	53.173	93.500	14.406	207.540	Normal distribution	27.100	-0.091	-0.130	66.600	16.030
Ni	13.000	24.979	47.00	5.115	26.162	Normal distribution	20.500	1.259	3.626	29.600	14.100
Zn	32.100	56.371	187.000	14.691	215.815	Lognormal distribution	26.100	4.810	39.922	71.100	7.050
Pb	10.700	17.631	45.900	4.045	16.365	Non-normal distribution	22.900	3.424	17.889	21.900	9.620
Cd	0.080	0.166	0.770	0.068	0.005	Lognormal distribution	41.000	4.830	39.852	0.100	95.150
As	2.900	9.514	18.600	2.719	7.391	Normal distribution	28.600	0.301	0.496	9.700	48.080
Hg	0.003	0.042	0.311	0.045	0.002	Lognormal distribution	108.4	3.805	17.024	0.047	21.790

Note: CV shows coefficient of variation; * shows Background value of fluvo-aquic soil in Henan Province

Table 4 shows that only the average Cd content exceeded the background value in the study area, manifesting that the soil quality was good. According to the heavy metal study analysis in 156 soil samples, the maximum exceeding rate of Cd was 95.51%, and the exceeding rates of other heavy metal elements were As (48.08%)>Hg (21.79%)>Cr (16.03%)>Ni (14.10%)>Cu (10.26%)>Pb (9.62%)>Zn (7.05%), indicating that Cd and As were the most serious pollutants in the low-lying land. The coefficient of variation (CV) is the ratio of the standard deviation of the original data to the average of the original data, indicating the dispersion degree of the data. CV of soil heavy metals were Hg (108.4%)>Cd (41%) >Cu (35.6%)>As (28.6%)>Cr (27.1%)>Zn (26.1%) >Pb (22.9%)>Ni (20.5%). Basing on the classification of the CV by Wilding [56], CV≤0.1 represent weak variability, 0.1<CV<1 represent medium variability, and CV≥1 represent strong variability. According to these classification criteria, Hg exhibited strong variability whereas the other seven heavy metals presented medium variability. This suggests that Hg is strongly affected by external disturbances and is greatly affected by human activities. For example, industrial activities and the excessive use of fertilizers. The normal distribution of 8 heavy metals was tested by the KS method. The results showed that Cr, Ni and As were normally distributed, Cu, Zn, Cd and Hg were lognormally distributed. Pb still did not meet the positive distribution after taking logarithm State distribution, therefore, it is not possible to use geostatistical Kriging interpolation for Pb space interpolation, but random model interpolation can be used.

Pollution Evaluation and Analysis of Spatial Interpolation Results

Comparison between Deterministic Interpolation and Geostatistical Kriging Interpolation

The selection of the optimal model needs to compare the average error, root mean square error and average standard deviation under different models. When the average prediction error is close to 0, it means that the prediction error is unbiased and optimal, but the size of the data will affect the average error. If it is affected, the closer the standard average error is to 0, the better; if the average error is close to the root mean square prediction error, the prediction standard deviation is effective, that is, the standardized root mean square error should be close to 1, and the prediction error can be judged Whether it is optimal. Therefore, the optimal model can be fitted when the standard average error (ME) is closest to 0; when the normalized root mean square error (RMSE) is nearest to 1; when the RMES and the ME are close and the minimum, the optimal model can be fitted.

According to the geostatistics analysis tool of ArcGIS 10.2 software, the inverse distance weighted interpolation method, global polynomial interpolation

Table 5. Optimal selection of deterministic interpolation and Kriging interpolation methods for heavy metal elements in soil.

Elements	Parameter	Interpolation method	ME	RMSE
Cu	IS	RBF	-0.076	6.101
	Constant	DK	-0.216	6.002
Cr	IS	RBF	-0.506	14.329
	Order 2	DK	-0.006	14.237
Ni	IS	RBF	-0.123	4.625
	Order 2	OK	-0.058	4.631
Zn	Order 4	GPI	1.259	13.600
	Order 1	UK	0.189	14.669
Cd	SWT	RBF	0.003	0.062
	Order 1	UK	-0.001	0.056
As	IS	RBF	-0.044	2.587
	Constant	UK	0.008	2.603
Hg	IS	RBF	-0.003	0.045
	Order 1	UK	-0.002	0.045
Pb	IS	RBF	0.063	3.885

Note: GPI: global polynomial interpolation; RBF: radial basis function interpolation; SWT: tension spline function interpolation; IS: anti high degree surface spline function; OK: Ordinary Kriging interpolation method; UK: Universal Kriging interpolation method; DK: Disjunctive Kriging interpolation method.

method and radial basis function interpolation method are OK, UK and DK in geostatistics. Three Kriging interpolation methods were used to determine the optimal interpolation method of 8 heavy metal elements in the soil of the study area according to the principle that the ME is closest to 0, the RMSE is the minimum, and RMSE is given priority [57]. The results are shown in Table 5.

It can be seen from Table 5 that the root mean square error of the DK under constant conditions is less than that radial basis interpolation method (RBF) of anti high degree surface spline function (IS); the average error of Cr element in the second order DK is the closest to 0, and the RMSE is the smallest. The RMSE value PBF of IS is less than DK. The RMSE of fourth order global polynomial interpolation (GPI) of Zn element is less than DK method of order 1. In the UK with the first-order trend effect, the ME value is the closest to 0 and the RMSE value is the smallest. The RMSE value of As element in the RBF of IS is less than that of UK under constant condition. The RMSE values of Hg element in the in the RBF of IS and the first order in UK are equal, but the me value of the first order UK is closer to 0. Pb

element does not conform to normal distribution, so it can not be used in linear Kriging interpolation method, but can be used the RBF of IS.

To sum up, the optimal interpolation methods of 8 kinds of soil heavy metal elements in the study area are: Cu is the DK of constant, Cr is the DK of order 2, Ni is RBF of IS, Zn is the GPI of order 4, Cd is the UK of order 1, As is the RBF of IS, Hg is the UK of order 1, Pb is RBF of IS.

Spatial Distribution Variation

According to the comparison of deterministic interpolation and Kriging interpolation in Table 5 under different parameters, the optimal interpolation method of eight heavy metal elements as obtained. The spatial distribution map of eight heavy metal elements in soil was obtained by using the optimal spatial interpolation model and the interpolation analysis tool of ArcGIS 10.2 software (Fig. 2).

Overall, the eight elements exhibited higher concentrations in the west, with lower concentrations in the east (Fig. 2). Moreover, all heavy metals presented
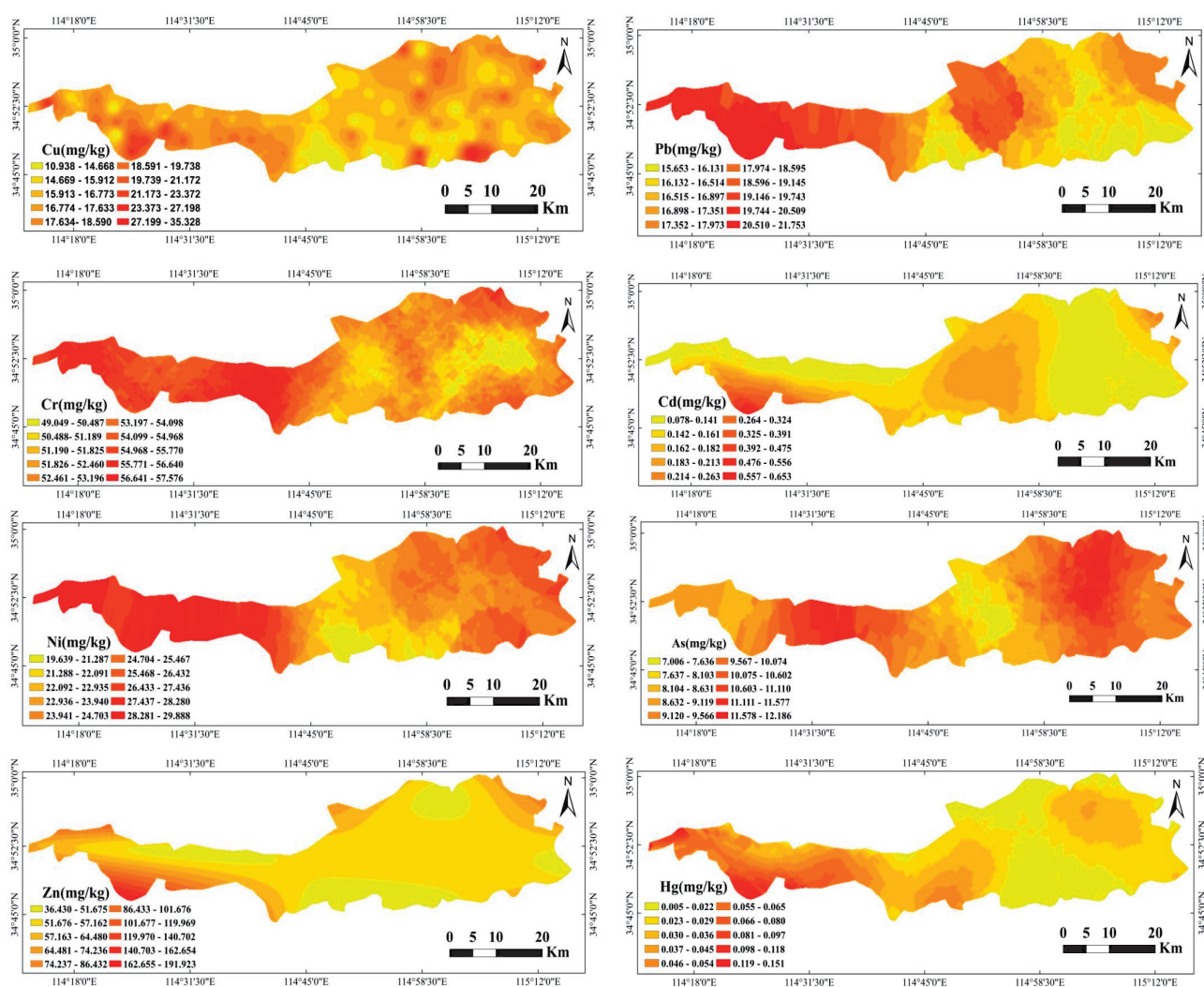

Fig. 2. Spatial distribution of heavy metal (Cu,Cr,Ni,Zn,Pb,Cd, As, and Hg) content.

Table 6. Descriptive statistics of single factor pollution index.

Elements	Minimum [mg·/kg]	Average [mg·/kg]	Maximum [mg·/kg]	Standard deviation	Variance	Skewness	Kurtosis
Cu	0.33	0.71	2.66	0.25	0.06	3.45	22.09
Cr	0.33	0.8	1.4	0.22	0.05	-0.09	-0.13
Ni	0.44	0.84	1.59	0.17	0.03	1.26	3.63
Zn	0.45	0.79	2.63	0.21	0.04	4.81	39.92
Pb	0.49	0.81	2.1	0.18	0.03	3.42	17.89
Cd	0.8	1.66	7.7	0.68	0.46	4.83	39.85
As	0.29	0.98	1.92	0.28	0.08	0.3	0.5
Hg	0.06	0.89	6.62	0.96	0.92	3.81	17.02

high concentration areas, suggesting the influence of human activities. The spatial variation of Zn, Cd, Pb, Hg, and Cu were similar. The area with the highest heavy metal concentrations were mainly located in the southwest area of the low-lying land, which was close to residential and industrial areas. Cr, Ni, and As also presented similar spatial distribution characteristics, which were found to be mainly sporadic, suggesting that it existed point source pollution. The heavy metal concentrations of western area of the low-lying land presented higher than the eastern area, likely because the western region encompasses a suburb of Kaifeng that is close to a coal chemical industrial area. This area also presents abundant industrial waste and automobile exhaust emissions, as well as garbage from households.

Pollution Assessment and Analysis of Spatial Distribution

Using the SPSS 20.0 software, descriptive statistical analysis were performed on the single factor pollution index of eight elements (Table 6).

Table 6 shows that among single factor pollution index of the eight elements examined herein, only the average value of Cd exceeded 1. According to the evaluation criteria, Cd concentrations fell within the slightly polluted classification. The average values of the remaining seven elements (i.e. Zn, Hg, As, Ni, Pb, Cu and Cr) were all less than 1, showing that they were within a safe level. The average value of As was 0.98, which is very close to the light pollution classification threshold. When accounting for maximum values of all heavy metals, the single factor pollution index examined herein exceeded 1 and therefore surpassed the threshold of light pollution. Notably, 7.7 and 6.62 were taken as maximum values of Cd and Hg, reaching the heavily contaminated classification, and Cu, Zn, and Pb reached the moderately contaminated threshold. These observations demonstrate that the eight soil heavy metals exhibited different degrees of pollution severity.

The individual pollution indexes of the eight heavy metals were determined basing on grading standard of the single-factor pollution index. The data suggest Cu presented 16 polluted points, and the percentage of pollution points was 10%. The number of polluted points for Cr was 24, and the percentage of polluted points was 15%. The number of polluted points for Ni was 21, and the percentage of polluted points was 13%. The number of polluted points of Zn was 11, the percentage of polluted points was 7%. Pb had 14 polluted points, and the percentage of pollution points was 9%. The total number of Cd polluted points was 145, and the percentage of polluted was 93%. The number of As polluted points was 73, and the total percentage of polluted points was 47%. Hg presented 34 polluted points, and the total percentage of polluted points was 22%.

In summary, upon completing single-factor rating analysis of the eight heavy metals, found Cd pollution was the most widespread, followed by Cr, Ni, and Hg with a somewhat high pollution point occurrence, and finally As, Cu, Zn, and Pb, which were found to be at relatively safe levels.

According to single factor pollution index classes that the spatial interpolation was carried out via the IDW of the ArcGIS 10.2 software to characterize the spatial variation (Fig. 3).

Fig. 3 shows that with the exception of Cd and As, the remaining six elements (i.e. Pb, Cr, Ni, Zn, Cu, Hg) in the study area mainly fell into the non-polluting category, whereas the study area was mainly classified as slightly polluted by Cd. This large-scale light Cd pollution in the study area may be overuse of pesticides and fertilizers. Cr, Ni, and As fell into the unpolluted and slightly polluted classifications. Cu, Zn, and Pb presented three pollution levels: unpolluted, slightly polluted, and moderately polluted. However, the area classified as moderately polluted was relatively small. Cd and Hg presented four pollution levels: unpolluted, slightly polluted, moderately polluted, and heavily polluted. The total area that was classified as heavily polluted by Hg was larger than that of Cd. Most of the Hg heavily polluted areas were closer to village roads, where there are more passing vehicles. Therefore,
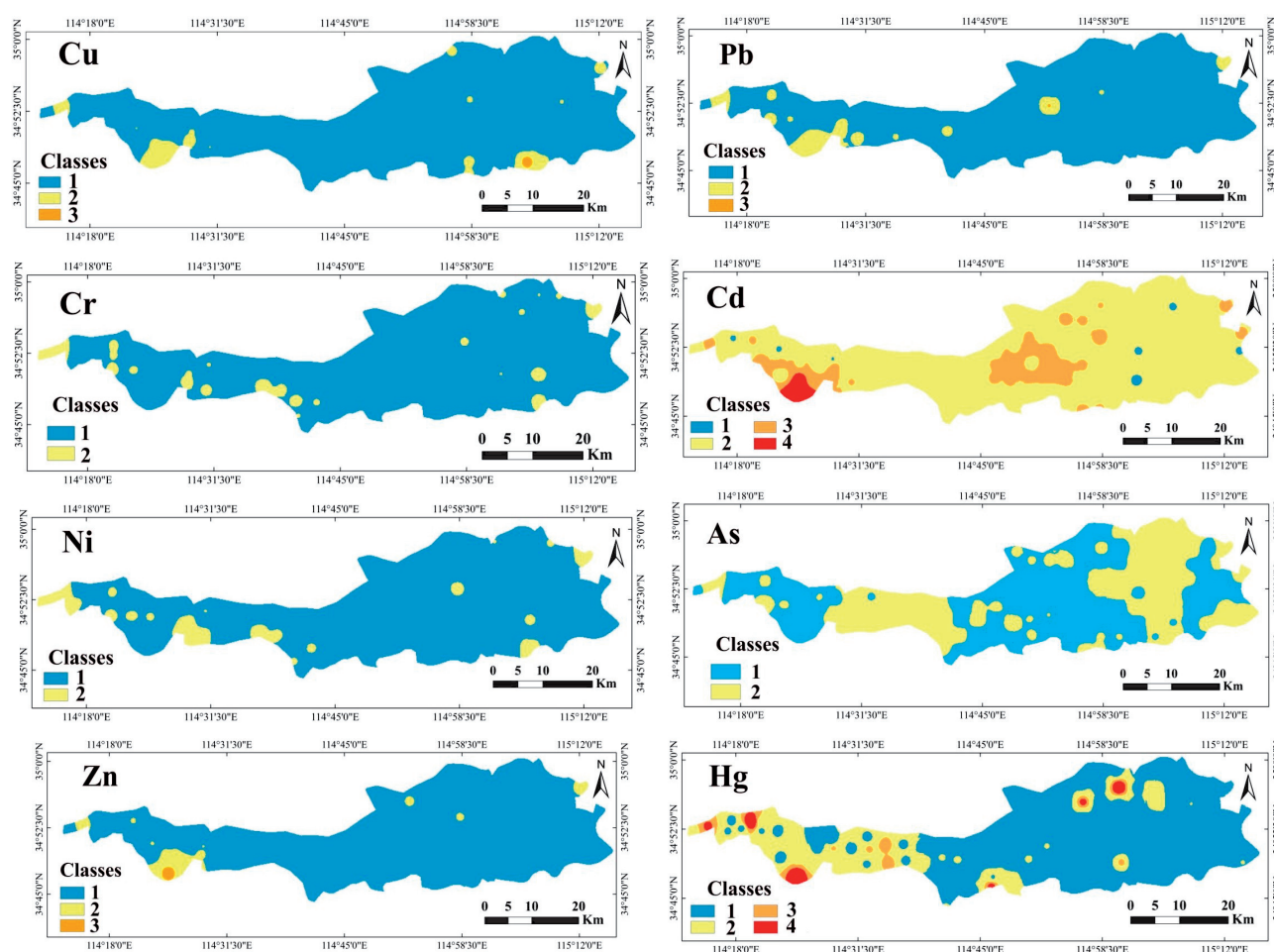
Fig. 3. Spatial distribution of single factor pollution index (Cu, Cr, Ni. Zn, Pb, Cd, As, Hg).

the main cause of Hg pollution may be automobile exhaust in said areas. Cd and Hg heavily polluted areas overlapped in the southwest region, which is a suburb with many residential areas and coal-fired enterprises 1.4 km away from the sampling point, suggesting that the main contributors of Cd and Hg pollution may be automobile exhaust and coal combustion in said area.

The value of the eight heavy metals were calculated according to Formula (2) to obtain the Nemerow comprehensive pollution index; the classification was then combined with the classification standard, after which the inverse distance weighted interpolation method based on the ArcGIS 10.2 software was used to make interpolation discuss on the classification results, as shown in Fig. 4.

Fig. 4 shows that the Nemerow index reached five levels. Most of the areas were classified as slightly polluted, areas of precaution were very few, and areas with safety levels were negligible, indicating widespread pollution of the soil in the study area. Heavily polluted
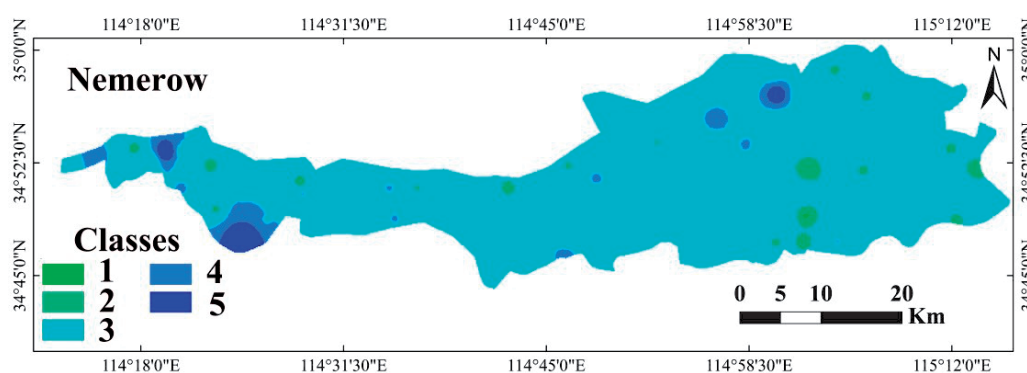

Fig. 4. Spatial distribution of Nemerow pollution index.

Table 7. Descriptive statistical results of soil heavy metal potential risk assessment.

Variables	Cu	Cr	Ni	Zn	Pb	Cd	As	Hg	RI
Minimum [mg/kg]	1.66	0.67	2.20	0.45	2.44	24.00	2.99	2.55	44.43
Maximum [mg/kg]	13.28	2.81	7.94	2.63	10.48	231.00	19.18	264.68	496.93
Average [mg/kg]	3.55	1.60	4.22	0.79	4.03	49.73	9.80	35.44	109.17
Standard deviation	1.27	0.43	0.86	0.21	0.92	20.36	2.80	38.41	52.51
Variance	1.60	0.19	0.75	0.04	0.85	415.98	7.86	1475.00	2757.76
Skewness	3.45	-0.09	1.26	4.81	3.42	4.83	0.30	3.81	3.96
Kurtosis	22.09	-0.13	3.63	39.92	17.89	39.85	0.50	17.02	22.41
Pollution degree	Low risk	Low risk	Low risk	Low risk	Low risk	Moderate risk	Low risk	Low risk	Low risk

areas coincided with regions with industrial activity, motorized transportation, densely populated residential areas, widespread human activities, automobile exhaust, industrial wastewater, domestic waste, and use of pesticides and fertilizers, all of which may have contributed to the pollution.

Evaluation of Potential Ecological Risk Indexes and Research of Spatial Distribution Characteristics

The reference value selected in the study is based on the background value of the fluvo-aquic soil in Henan Province, which can better reflect the regional differentiation. The potential ecological risk index value is based on the formula (3) to calculate using the SPSS 20.0 software and, according to the grading standards (Table 3), the ecological environment risk index value was subjected to descriptive statistical analysis and hierarchical evaluation. The results are shown in Table 7.

Table 7 shows that only Cd presented a moderate risk, whereas the other seven were all classified as having low risk. An comprehensive RI determined that the study area presented a low risk, indicating that heavy metal pollution poses a low environmental risk, most of which is attributable to Cd pollution. From a maximum value perspective, only Cd and Hg exceeded

a value of 40, reaching values of 231 and 264.68, respectively, both of which were classified as having a very strong risk potential. The maximum values of the other six elements were classified as having a low risk that the reason was value less than 40. This indicates that Cd and Hg present strong risks to different degrees, which is related to the higher toxicity of Cd and Hg. Taking the minimum value as reference, all eight heavy metals examined in soil were below a value of 40, which is associated with a low risk. The maximum value of the RI was 496.93, which corresponds with a very strong risk, according to the classification standard. The RI also exhibited strong risks at different levels, which was mainly reason what because the maximum values of Hg and Cd were large.

IDW of the ArcGIS 10.2 software was used to make interpolation research on the classification results to obtain a potential ecological pollution index classification map, as shown in Fig. 5.

Fig. 5 shows that the potential ecological risk index level was mainly dominated by low risk areas, followed by moderate risk areas. Only a few strong risk areas were identified, very strong risk areas were negligible. Low risk areas were mainly concentrated in the eastern region, specifically in the Lankao County (Kaifeng, China) area. Ecological risk was mainly moderate in the western area of the low-lying land, where corresponds
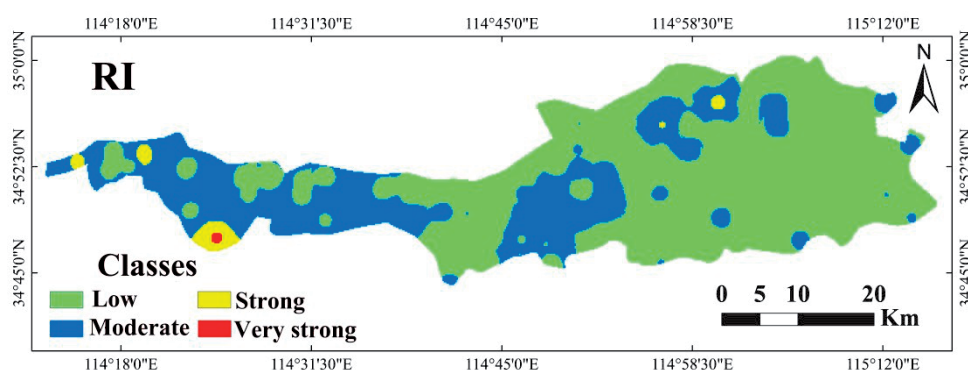

Fig. 5. Spatial distribution of potential ecological risk index.

Table 8. Results of the correlation analysis.

Elements	Cu	Cr	Ni	Zn	Pb	Cd	As	Hg
Cu	1							
Cr	0.346**	1						
Ni	0.607**	0.704**	1					
Zn	0.571**	0.443**	0.584**	1				
Pb	0.485**	0.408**	0.588**	0.682**	1			
Cd	0.402**	0.272**	0.289**	0.808**	0.623**	1		
As	0.341**	0.499**	0.565**	0.292**	0.195*	0.091	1	
Hg	0.222**	0.167*	0.195*	0.439**	0.362**	0.437**	0.037	1

Note: ** indicates significant correlation at a 0.01 level; * indicates significant correlation at a 0.05 level.

Table 9. Principal component analysis results.

Factor	Initial eigenvalue			Extract square sum load			Rotate square sum load		
	Eigenalues	Variance (%)	Cumulative Variance(%)	Eigenvalues	Variance (%)	Cumulative Variance (%)	Eigenvalues	Variance (%)	Cumulative Variance (%)
1	4.037	50.458	50.458	4.037	50.458	50.458	2.832	35.403	35.403
2	1.460	18.253	68.711	1.460	18.253	68.711	2.665	33.308	68.711
3	0.709	8.863	77.757						
4	0.589	7.360	84.935						
5	0.512	6.401	91.336						
6	0.373	4.662	95.998						
7	0.209	2.614	98.612						
8	0.111	1.388	100.00						

to the suburbs of Kaifeng City. The strong and very strong risk areas corresponded with the residential regions of villages within the city. These observations demonstrate that potential ecological risks were greatly affected by human activities.

Using the SPSS 20.0 software to study correlation analysis and principal component analysis of the eight elements in the low-lying land. According to these results that we can decide source analysis of heavy metals in soil. The results are shown in Tables 8 and 9.

Table 8 shows that the correlation between Cd and As was weak and not significant. Meanwhile, no significant correlation between As and Hg was identified. In general, with the exception of As, Cd, and Hg, which had no significant correlation between the eight heavy metals, other heavy metals exhibited significant or extremely significant positive correlations. These observations suggest that the pollution sources of Zn, Ni, Cu, Pb, and Cr may come from the same category.

Table 9 shows that two-component factors were extracted from eight components in the study area, and the cumulative variance was 68.711%. the variance

contribution rate of factor 1 (extracted square sum) was 50.458%, and the variance contribution factor of factor 2 (extracted square sum) was 18.253%. The factor load matrix is more clearly distributed after rotation (Table 10), which can better explain the meaning

Table 10. Comparative analysis between factor loadings and extraction sums of squared loadings.

Elements	Component matrix		Rotation component matrix	
	PC1	PC2	PC1	PC2
Cu	0.877	-0.27	0.465	0.554
Cr	0.816	0.416	0.190	0.791
Ni	0.796	-0.224	0.311	0.862
Zn	0.718	0.086	0.825	0.402
Pb	0.714	-0.530	0.735	0.381
Cd	0.679	0.447	0.883	0.101
As	0.507	0.647	-0.073	0.819
Hg	0.473	-0.506	0.691	-0.046

of each factor than when rotation was not applied. Therefore, load matrix rotation was used to interpret and analyze the eight heavy metals. Zn, Pb, Cd, and Hg with larger load values in the first principal component (PC1) exhibited a variance contribution rate of 35.403%, suggesting that the pollution sources of these four elements may be the same; the second main component (PC2) had larger load values for Ni, Cr, Cu, and As, and the variance contribution rate was 33.308%, suggesting that these four heavy metals may share similar sources. Compared with the results of the correlation analysis, only As had no significant correlation with Pb and Hg, further suggesting that the pollution sources of these two groups of factors are the same or similar.

Combined with the previous analysis, only the average Cd concentration exceeded the background value, and the rate of sample exceeding the standard reached 95.51%. Cd is often used as an indicator of excessive fertilizer and pesticide use [58], and therefore the occurrence of Cd is linked to human activities. Regarding the degree of variation, the coefficient of variability of Hg was the highest, which also suggests that the concentrations of this heavy metal are greatly affected by human activity. Hg accumulation in heavily polluted areas was mostly distributed in residential areas, where motorized vehicles are common. Therefore, it can be inferred that the sources of Hg pollution mainly come from automobile exhaust, domestic waste, industrial waste gas, and others. The single factor index indicates that Cu, Cr, Ni, and As pollution was light, and that there were no instances of medium or heavy pollution, showing that the concentrations of these elements are greatly affected by natural sources. In summary, Zn, Pb, Cd, and Hg in the first principal component (PC1) of the study area are greatly affected by anthropogenic sources, and Cu, Cr, Ni, and As in the second principal component (PC2) are greatly affected by natural sources.

Conclusions

In this research, 156 soil samples were acquired from a typical landform in the lower Yellow River Basin to analyze heavy metal concentrations. We measured reight element contents (Hg, Zn, Ni, Cr, Cd, Cu, As and Pb) and used the background value of the fluvo-aquic soil in Henan Province to compare, after which SPSS 20.0 and ArcGIS 10.2 were used to characterize the spatial variation of the Nemerow pollution indexes. Then we discussed the pollution status and spatial distribution characteristics. And we also evaluated the potential ecological risk of soil in the low-lying land. Furthermore, according to correlation analysis and principal component analysis, we identified the source of soil heavy metals in the study area. Based on the background value of soil heavy metals to compare,

the overall exceeding rate was not high. Only Cd exceeded the average pollution content, whereas Hg, As, Cu, Cr, Ni, Pb, and Zn did not surpass the background value.

The optimal interpolation models of eight heavy metals in the study area are: t Cu is the DK of constant, Cr is the DK of order 2, Ni is RBF of IS, Zn is the GPI of order 4, Cd is the UK of order 1, As is the RBF of IS, Hg is the UK of order 1, Pb is RBF of IS. The eight elements in the low-lying land exhibited higher values in the west, with lower values in the east; all heavy metals exhibited high-value zones, indicating that the prevalence of human activities in the highly polluted areas has a substantial affect. Cr, Ni, and As may result from point source pollution in the low-lying land. The comprehensive assessment of soil heavy metal pollution indicated that the total pollution ratio was 80.13%, showing that much of the study area is slightly polluted. The heavily polluted areas in the study area mainly coincided with industrial zones and densely populated areas, where motorized vehicles and other human activities are relatively prevalent. Only Cd had reached a moderate risk level based on the potential ecological risk assessment in the low-lying land, whereas the other seven elements pose a low risk. A comprehensive potential ecological risk assessment also demonstrated that there is an overall low risk linked to heavy metals, with Cd being the main risk factor in the area. Moreover, although there was no significant correlation between As, Hg, and Cd, other heavy metals exhibited a significant or very significant positive correlation. Hg, Cd, Zn and Pb were greatly affected by anthropogenic sources, and Ni, Cu, Cr, and As were greatly affected by natural sources.

Conflict of Interest

The authors declare no conflict of interest.

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