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Analysis of Heavy Metal Sources and Sustainability: Human Health Risk Assessment of Typical Agricultural Soils in Tianjin, North China Plain

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Abstract: Tianjin is a typical industrialized city of 13.64 million people, and the urbanization rate is 85.49%. The risk of heavy metals in the soils of the typical agricultural land around Tianjin poses a significant challenge to the sustainability of the ecosystem's health and human health. Different heavy metals in different land-use types in Tianjin have all accumulated in the soils, and the vegetable base had the highest total of accumulated heavy metals. This study took the surface soil of farmland Xiqing District—the main vegetable and crop area in Tianjin—as the research object, and the concentrations of eight heavy metals were analyzed. The geo-accumulation index (I_{geo}), principal component analysis (PCA), absolute principal component score-multiple linear regression (APCS–MLR), positive definite matrix factorization (PMF), and health risk assessment model were used to evaluate the degree, sources, and health risks (to adults and children) of heavy metal pollution. This study compares the APCS–MLR model with the PMF model. The results showed that Cd and Hg pollution were the most severe among the eight heavy metals in agricultural soil, with the average values exceeding the background by 151.9% and 324.1%, respectively. About 15% of the sites were at moderate to severe pollution levels. The PMF model can better analyze the sources of heavy metals in the study area, showing that the main sources of heavy metal pollution include natural source, mixed source of agriculture and transportation, coal combustion source, and pesticide source. The total carcinogenic risk index (TCR) of natural source is the highest, with Cr being the main contributor to maximum total non-carcinogenic risk indices (HI) and TCR for children; Hg contributes the most to HI in the coal combustion source, while Cu and Zn contributes most in the mixed source of agriculture and transportation.

Keywords: agricultural land; heavy metals; APCS–MLR; PMF; health risk assessment

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1. Introduction

Heavy metals pollution of farmland soil is becoming an increasingly serious concern in China. Heavy metals continuously accumulate throughout the food chain [1] and enter into the human body, seriously affecting human health [1–9]. The accurate assessment of heavy metals in soil, the source composition and the ecological environmental risks in soil are the foundations of soil pollution prevention [10–15]. Some studies have analyzed the farmland soil heavy metal content and sources of different places in China [16–21].

Absolute principal component score–multiple linear regression (APCS–MLR) and positive matrix factorization (PMF) models were used to analyze the pollution sources in various media such as the atmosphere, water, and soil, especially in the contribution rate of potential sources of heavy metals in soil [22–32].

Tianjin is a historically industrial city, and some studies have focused on the heavy metal pollution and sources. For example, Li [33] studied the pollution characteristics of heavy metal in different land-use types in Tianjin, showing different heavy metals had accumulated in soils, but the overall pollution level in Tianjin was lower. However, vegetable base had the highest total accumulation of heavy metal. Zhang and other's studies [34–38] showed the content of Cd, Pb and As in the suburb farmland soils of Tianjin have exceeded the standard and are significantly affected by human activities. Thus, attention is needed in the management and administration of the soils because this heavy metal pollution will harm human health. However, there are still some shortcomings in the literature, namely the following: (1) The studies rarely compare different models to enhance the validity of a conclusion. (2) To analyze their systematic correlation, the studies have only considered potential ecological risks in assessing heavy metals in agricultural soil, without organically combining the contribution rate of source apportionment with human health risks [39–44]. (3) The human health risks caused by hand-to-mouth ingestion, breath ingestion and skin contact exposure pathways have not been considered, and it is impossible to estimate the quantified health risks of adults and children from different sources, which can't be ignored in the evaluation process. The heavy metal pollution in farmland soil and human health risk assessment should receive widespread attention from the governmental administration.

In this study, the largest agricultural product planting area in Tianjin was selected as the research area. Eight heavy metals (Cd, Cr, Cu, Ni, Pb, Zn, As, and Hg) were selected as the research objects. APCS–MLR and PMF models were used to qualitatively and quantitatively study the sources of heavy metal pollution. The results of the two models were compared to determine whether there is consistency in the main sources (such as industrial activities, pesticides and fertilizers, transportation emissions, and so on), and explore whether industrial emissions or fertilizer and pesticide application are the primary factors of heavy metal pollution. An optimized source contribution-oriented health risk assessment model was used to quantify the health risk values of adults and children from different sources. Source apportionment and health risk assessment were conducted on soil heavy metals in the study area, combined with spatial correlation, providing a scientific basis for the study of heavy metal pollution, food safety, and human health in agricultural land in Tianjin, North China Plain

2. Materials and Methods

2.1. Study Area

As shown in Figure 1, the study area is located in Yangliuqing Town and Xinkou Town, Xiqing District, Tianjin, North China Plain. It is the main vegetable and crop area in Tianjin, and also a part of the basic farmland protection zone in Tianjin. The current land-use in this area is diverse, with much residential land and a small number of industrial enterprises distributed in the surrounding area. The region is in the temperate continental semi-arid monsoon zone, with average annual temperature of 11.9 °C and average annual rainfall of 542.6 mm (75 percentage in summer). Northwest wind prevails in winter, southeast wind in summer, and southwest wind in spring and autumn in the study region. The local soil type is fluvo-aquic and the parent material of the soil is modern river alluvium. The ground water is about 1.5~2.5 m deep. Corn, vegetables and fruit trees are the main plants in the region, and vegetables are mainly planted in greenhouses in winter. The Ziya River and

the Zhongting River go through the study area, and they are the main sources of irrigation water for farmland. In the study area, nitrogen fertilizer, potassium fertilizer, phosphorus fertilizer, and compound fertilizer are used, and the proportion is determined according to the plant species.

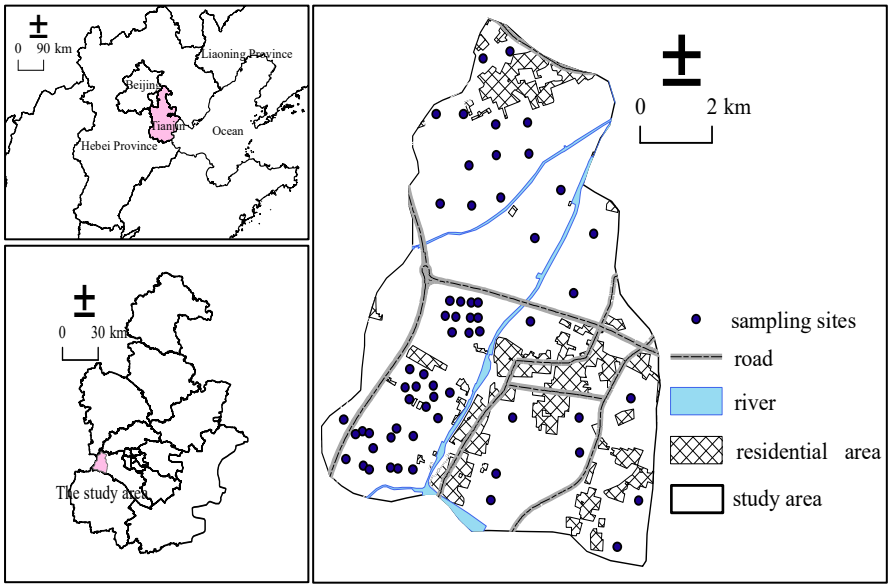


Figure 1. Schematic distribution of sampling points in the study area.

2.2. Sampling and Analysis

Farmland in Xinkou Town and Yangliuqing Town were selected, with a grid network of 100 m × 100 m. A total of 60 soil surface samples (0~20 cm) (as shown in Figure 1) were collected from July to September in 2022. Each sample was a mixture of three subsamples around the sample site. All samples were collected with a wooden spatula and kept in polyethylene bags. Soil was dried naturally in the laboratory after removal of plant residues and gravel. The dry samples were ground and passed through a 100-mesh nylon sieve.

Inductively coupled plasma optical emission spectrometry (ICP-OES) (U.S.EPA Method 6010D-2014) [45] was used to measure the content of Cr, Cu, Ni, Pb, Zn; microwave dissolution/atomic fluorescence spectrometry (HJ 680-2013) [46] was used to measure the content of As, Hg; inductively coupled plasma mass spectrometry (ICP-MS) was used to measure the content of Cd; potentiometry was used to measure the pH values of all samples.

2.3. Research Methods

2.3.1. Geo-Accumulation Index (I_{geo})

Study area pollution assessment is conducted with a geo-accumulation index (I_{geo}). I_{geo} can not only be used to evaluate the distribution of heavy metals in the sediments but also assess the impact of human activities on the environment [47,48]. I_{geo} is a classical method widely used for assessing the soil pollution level of selected elements; the relevant equation is as follows:

$$I_{geo} = \log_2 \frac{C_i}{1.5B_i} \quad (1)$$

where C_i represents the concentration of the heavy metal element i (mg·kg^{-1}); B_i represents the background value of the heavy metal i (mg·kg^{-1}). I_{geo} can be classified into seven levels [49], as shown in Table 1.

Table 1. Levels of geo-accumulation index (I_{geo}).

I_{geo}	$I_{geo} < 0$	$0 \leq I_{geo} < 1$	$1 \leq I_{geo} < 2$	$2 \leq I_{geo} < 3$	$3 \leq I_{geo} < 4$	$4 \leq I_{geo} < 5$	$I_{geo} \geq 5$
Pollution levels	Level I: Uncontaminated	Level II: Uncontaminated to moderately contaminated	Level III: Moderately contaminated	Level IV: Moderately to heavily contaminated	Level V: Heavily contaminated	Level VI: Heavily to extremely contaminated	Level VII: Extremely contaminated

2.3.2. Pearson Correlation Coefficient

The Pearson Correlation Coefficient (r) is the statistical standard for measuring the degree of linear relationship between two variables. This coefficient provides a numerical summary ranging from −1 to +1, where each endpoint represents a perfect linear relationship, either negative or positive. An "r" value of 0 indicates no linear correlation between the variables. It reflects how much one variable can predict another through a linear equation. In practice, the value of "r" guides analysts in determining the predictability and strength of the relationship, offering a foundation for further statistical modeling and inference.

2.3.3. Principal Component Analysis

Principal component analysis is used to analyze the principal component quantity and composition of heavy metal content data in soil. It extracts the characteristic vector of the main variance in the composition of heavy metal content as the principal component [50–52], so as to identify the main influencing factors and sources of the heavy metals. The Kaiser–Meyer–Olkin (KMO) value of the samples is 0.813, and in the Bartlett's test of sphericity, the value of p is zero, indicating that the testing results of elements can be analyzed with the principal component analysis method.

2.3.4. APCS–MLR Model

The absolute principal component score–multiple linear regression (APCS–MLR) model is used to analyze the concentration of heavy metal in the study area. The basic principle of APCS–MLR model is to convert the principal factor score of factor analysis into an absolute principal component score (APCS), then, take APCS as the independent variable and the content of each heavy metal element as the dependent variable. In the following, multiple linear regression analysis was performed, obtaining the contribution rates of different pollution sources.

Data standardization and extraction of principal components are as follows:

$$A_{zk} = \sum_{j=1}^{n} (w_j \times z_k) \quad (2)$$

Artificial samples with a content of 0 and factor scores for heavy metal content of 0 were injected as follows:

$$A_{zk} = \sum_{j=1}^{n} (w_j \times z_k) \quad (3)$$

where z_k is the standardized concentration value of element j in sample k; w_j is the factor coefficients of principal component j; A_{zk} is factor score of principal component p for element j; S_{ij} is the factor score coefficient of principal component j in element i; A_{0j} is the factor score of principal component j at 0 concentration.

When the concentration is 0, the factor score of the principal component minus the factor score of the component obtained is the absolute principal component score (APCS). Take APCS as the independent variable and the content of each heavy metal element

as the dependent variable to perform multiple linear regression analysis, obtaining the contribution rates of different pollution sources as follows:

$$APCS_{jk} = A_{z_{jk}} - A_{0j} \tag{4}$$

$$\omega_{\mathrm{i}} = \sum_{m=1}^{n} (a_{im} \times APCS_{im}) + b_i \tag{5}$$

where $APCS_{jk}$ is the absolute principal component score of principal component j in sample k, A_{zjk} is the score of component j in sample k, ω_i is the measured content of heavy metal i, b_i is the constant term of multiple regression, a_{im} is the regression coefficient of pollution source m for heavy metal i, $APCS_{im}$ is the absolute principal component score, n is the number of factors, and $a_{im} \times APCS_{im}$ is the contribution rate of pollution source m to ω_i.

The product of a_{im} and $APCS_{im}$ is the contribution of pollution sources to heavy metal element factors. The contribution rate of pollution source m to heavy metal i is calculated as follows:

$$P\omega_{im} = \frac{\left|a_{im} \times \overline{APCS_{im}}\right|}{|b_i| + \sum_{m=1}^{n}\left|a_{im} + \overline{APCS_{im}}\right|} \tag{6}$$

where b_i is the unrecognized source contribution (unrecognized source), the unrecognized source contribution is calculated as follows:

$$P\omega_{im} = \frac{|b_i|}{|b_i| + \sum_{m=1}^{n}\left|a_{im} + \overline{APCS_{im}}\right|} \tag{7}$$

$P\omega_{im}$ is the contribution rate of heavy metal element i in pollution source m, $APCS$ is the average absolute principal component factor score of all samples of heavy metal i.

2.3.5. PMF Model

Positive definite matrix factor analysis (PMF) is a data analysis method based on the principle of factor analysis and is widely used in pollution source analysis [53]. It can be resolved into two factor matrices: F_{kj}, and G_{ik}, and a residuals matrix E_{ij}, the relevant equation is as follows:

$$X_{ij} = \sum_{k=1}^{p} G_{ik}F_{kj} + E_{ij} \tag{8}$$

where X_{ij} is the concentration of element j in sample i, G_{ik} is the concentration contributed by source k to the i sample, F_{kj} is the content of the j element in the source, and E_{ij} is the residuals matrix that is not accounted for by the model. The objective function Q, which is defined by PMF, is expressed by the following equation:

$$Q = \sum_{i=1}^{n}\sum_{j=1}^{m}\left(\frac{e_{ij}}{u_{ij}}\right)^2 \tag{9}$$

where u_{ij} is the uncertainty of element j in sample i, e_{ij} is the uncertainty of the model. In addition, uncertainties of all elements (U_{nc}) are needed, and the relevant equation is as follows:

$$U_{nc} = \sqrt{(\theta \times X_{ij})^2 + (MDL)^2}\ (X_{ij} > MDL)$$

$$U_{nc} = \frac{5}{6} \times MDL\ (X_{ij} \leq MDL) \tag{10}$$

where θ is the relative standard deviation, X_{ij} is the content of every element, and MDL is the corresponding method detection limit.

2.3.6. Comparison Between Two Models

The APCS–MLR model converts the scores from principal component analysis into absolute factor scores. These absolute factor scores serve as independent variables, while the measured heavy metal concentrations are the dependent variables. A multiple linear regression model is established to determine the contribution of each pollution source to each heavy metal. Thus, it can identify the number of factors and better explain the contribution rate of heavy metal sources. However, the source contribution estimates can be negative; the existence of these negative contributions, despite being right, might lead to confusion in the interpretation and analysis of the source apportionment results [54].

PMF model works by imposing non-negative constraints on the concentration matrix of the chemical species detected at the receptor sites, which is the result of the product of source composition and contribution factor matrices plus a residue matrix [55].

The PMF model has no method to determine the reasonable number of factors; however, it can individually weigh each data point, and it allows for adjustment of the influence of each data point, avoiding negative values during the matrix factorization process.

Thus, it is important to compare different models in order to enhance the validity of a conclusion [54].

2.3.7. Health Risk Assessment

The United States Environmental Protection Agency (USEPA) health risk assessment model [56] is used in this study to assess soil health risks. The calculation method for daily average exposure of soil heavy metals under various exposure pathways is calculated as follows:

$$ADD_{ing} = \frac{C \times R_{ing} \times EF \times ED}{BW \times AT} \times 10^{-6} \quad (11)$$

$$ADD_{inh} = \frac{C \times R_{inh} \times EF \times ED}{PEF \times BW \times AT} \quad (12)$$

$$ADD_{der} = \frac{C \times SA \times AF \times ABS \times EF \times ED}{BW \times AT} \times 10^{-6} \quad (13)$$

where ADD_{ing}, ADD_{inh}, and ADD_{der} are the average daily dose of heavy metals via hand-to-mouth ingestion, breath ingestion and skin contact, mg/(kg·d). The health risk exposure parameters of heavy metals are shown in Table 2.

Table 2. Health risk exposure parameters of heavy metals.

Symbol	Parameter	Reference Value for Adults	Reference Value for Children
EF	exposure frequency/(d/a)	300	300
ED	exposure duration/a	24	6
AT	average time/d	365 × 24	365 × 6
BW	body weight/kg	5	15
R_{ing}	daily intake of soil in hand and mouth/(mg/d)	100	200
R_{inh}	respiratory rate/(m^3/d)	20	5
PEF	particle emission factor/(m^3/kg)	1.36×10^9	1.36×10^9
AF	Adherence factor to skin/[mg/(cm^2·d)]	0.07	0.2
SA	skin surface area exposed/cm^2	4350	1660
ABS	dermal absorption factor	0.001	0.001

Cd, Cr, Hg, Ni, Pb, As, Cu and Zn all have chronic non-carcinogenic risk, Cd, As, Cr and Ni have carcinogenic risk, hazard quotient (*HQ*), hazard index (*HI*) and total cancer risk (*TCR*) were used to assess the toxic effects of human exposure to pollutants as follows:

$$HI = \sum \frac{ADD_i}{RfD_i} \tag{14}$$

$$TCR = \sum CR = \sum ADD_i \times SF_i \tag{15}$$

where *HI* is the total non-carcinogenic hazard attributable to exposure to a specific exposure pathway, *TCR* is the total cancer risk from multiple exposure pathways, RfD_i is the reference dose for heavy metals via pathway *i*, mg/(kg·d), and SF_i is the slope factor of heavy metals via pathway *i*, (kg·d)/mg. The RfD_{ing}, RfD_{inh}, RfD_{der} values of different metals are Cd (1.00×10^{-3}, 1.00×10^{-3}, 1.00×10^{-5}), Hg (3.00×10^{-4}, 1.50×10^{-5}, 8.60×10^{-5}), As (3.00×10^{-4}, 1.23×10^{-4}, 3.00×10^{-4}), Pb (3.50×10^{-3}, 3.52×10^{-3}, 5.22×10^{-4}), Cr (3.00×10^{-3}, 2.86×10^{-5}, 6.00×10^{-5}), Cu (4.00×10^{-2}, 4.02×10^{-2}, 1.20×10^{-2}), Ni (2.00×10^{-2}, 2.06×10^{-2}, 5.40×10^{-3}), Zn (3.00×10^{-1}, 3.00×10^{-1}, 6.00×10^{-2}), and the SF_{ing}, SF_{inh}, SF_{der} values of different metals are Cd (6.1, 1.80×10^{-3}, 6.1), As (1.5, 4.30×10^{-3}, 1.5), SF_{inh} (Cr) is 42 and SF_{inh} (Ni) is 8.40×10^{-1}. Non-carcinogenic risk can be ignored when $HQ \leq 1$, and there's non-carcinogenic risk when $HQ > 1$; non-carcinogenic risk can be ignored when $HI \leq 1$, and there's non-carcinogenic risk when $HI > 1$. When $CR < 10^{-6}$, there isn't carcinogenic risk, when $10^{-6} < CR < 10^{-4}$, carcinogenic risk is within an acceptable range, when $CR > 10^{-4}$, things which are exposed to the surroundings will suffer carcinogenic risk. When $TCR < 10^{-6}$, there isn't carcinogenic risk, when $10^{-6} < TCR < 10^{-4}$, carcinogenic risk is within an acceptable range, when $TCR > 10^{-4}$, things which are exposed to the surroundings will suffer carcinogenic risk.

Kriging is a commonly used method of interpolation (prediction) for spatial data. The data are a set of observations of some variables of interest, with some spatial correlation present. Usually, the result of kriging is the expected value ("kriging mean") and variance ("kriging variance") computed for every point within a region. In order to predict the values in Tianjin by using the values at the measured location (the study area), ArcGIS (10.7) was employed to calculate by using the kriging interpolation method.

3. Results and Discussion

3.1. Characteristics Analysis of Heavy Metal Content in Soil

Table 3 shows the characteristics of heavy metal concentration and the statistics. The concentration of Hg, Cd, Zn, Cu and Pb exceed the background values obviously, and the excess rates are Hg (324.1%) > Cd (151.9%) > Zn (45.4%) > Pb (32.2%) > Cu (27.0%), indicating the relatively high degree of accumulation for Hg, Cd, Zn, Cu and Pb, especially for Hg and Cd.

Maximum concentration of Cd exceeds the risk intervention value, and maximum concentrations of other heavy metals are lower than the risk screening values according to (GB 15618-2018). Coefficient of variation (CV) can be used to assess the interference of human factors on the accumulation [47,48]. The values of all elements range from 0.12 to 1.62, and are sorted by Hg > Cd > Zn > Cu > Pb > As > Ni > Cr. The values of Hg and Cd are higher than the others, indicating the two elements are more easily affected by human influence.

Table 3. Descriptive statistical characteristics of heavy metals.

Element	Mean/ (mg/kg)	Range/ (mg/kg)	Standard Deviation/ (mg/kg)	Coefficient of Variation	Kurtosis	Skewness	Background Values */ (mg/kg)	RSV #/ (mg/kg)	RIV #/ (mg/kg)
Cd	0.23	0.08~0.84	0.12	0.51	11.98	2.61	0.09	0.6	4
Cr	66.8	47.3~81.2	7.94	0.12	−0.43	−0.46	98.38	250	1300
Hg	0.212	0.011~2.29	0.34	1.62	23.38	4.32	0.05	3.4	6
Ni	32.9	22.3~42.9	5.95	0.18	−1.16	−0.19	34.46	190	/
Pb	26.9	16.8~50.4	6.13	0.23	2.41	1.07	20.32	170	1000
As	10.6	6.1~15.1	2	0.19	−0.58	−0.04	11.07	25	100
Cu	36.1	16.4~64.8	11.18	0.31	0.06	0.4	28.38	100	/
Zn	111	55.7~246	40.37	0.36	0.84	0.91	76.27	300	/

* Soil background of Tianjin [57]; # Risk control standard for soil contamination of agricultural land (GB15618-2018) [58] pH > 7.5.

In this area, optimized fertilization [59] and "production while repairing" [60] can be introduced.

3.2. The Geo-Accumulation Indices (I_{geo})

Figure 2 illustrates the I_{geo} value and levels of heavy metals in soil. The I_{geo} ranges of Cr and Ni are −1.64~−0.86 and −1.09~−0.14, respectively, which are all at the uncontaminated level, and means the two elements are less affected by human activities. The I_{geo} ranges of Pb and As are −0.74~0.87 and −1.22~0.08, respectively, which are in level I to II, and the I_{geo} ranges of Cu and Zn are −1.38~1.09 and −0.97~1.28, respectively, which are in level I to III, and the four elements are all probably affected by human activities. The I_{geo} ranges of Cd and Hg are −0.43~3.28 and −1.84~3.09, respectively, with a large fluctuation (15% of the sites are in moderately to heavily contaminated class) indicating the elements Cd and Hg are greatly affected by human activities.

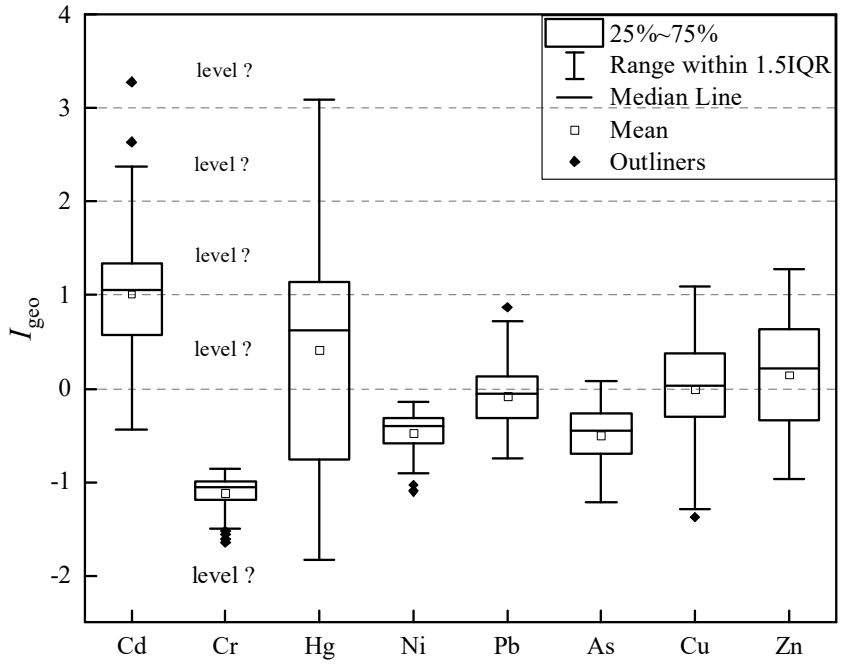


Figure 2. The I_{geo} values and levels of heavy metals in soil.

3.3. Correlation Analysis of Heavy Metal Interactions

Figure 3 is the Pearson correlation analysis of eight heavy metals. If the correlation between two elements is significant, the two elements have similar geo-chemical behaviors, such as source or migration [61]. The correlations of Cd–Pb, Cd–Cu, Cd–Zn, Cr–Ni, Cr–As, Pb–Cu, Pb–Zn, and Cu–Zn are strong ($r > 0.60$, $p \leq 0.\ 01$), indicating these elements possibly come from the same source. The correlations of Cd–Cr, Cd–Hg, Cd–Ni, Cd–As, Cr–Pb, Cr–Cu, Cr–Zn, Hg–Pb, Ni–Pb, Ni–Cu, Ni–Zn, Pb–As, As–Cu, and As–Zn are moderate ($0.30 < r \leq 0.60$, $p \leq 0.01$), indicating these elements may come from the same source and there is a possibility of composite sources. The correlation coefficient value of Ni–Hg is negative (−0.11), indicating it is almost impossible that they come from the same source.

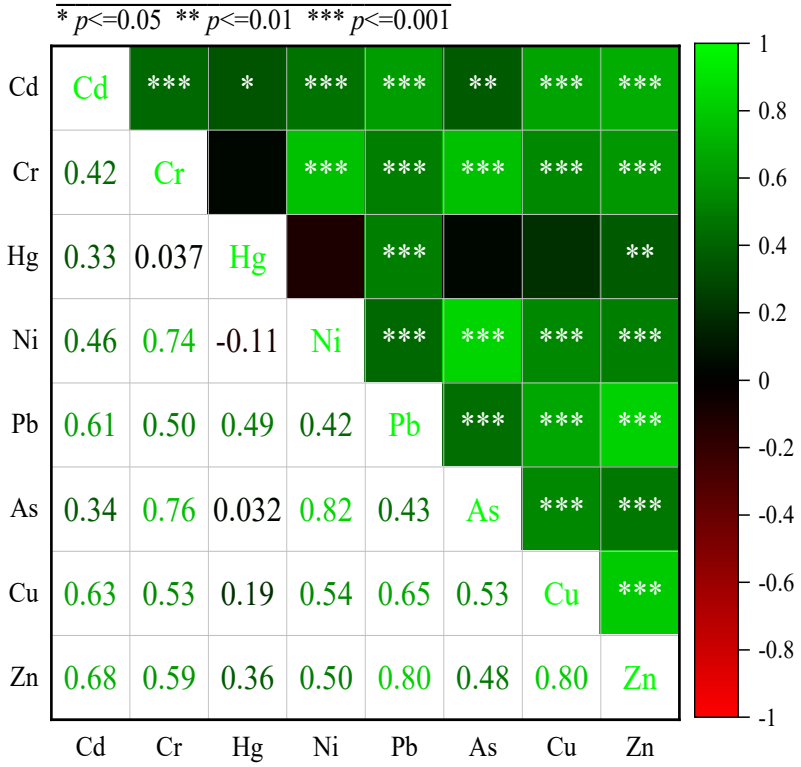


Figure 3. Pearson correlation analysis of eight heavy metals.

3.4. Principal Component Analysis

Table 4 shows the load and contribution rate of main components after being spun. The first three factors' accumulated contribution rate of variances was 84.6%, showing that the main factors fit the original variables well, so the first three factors were chosen.

Table 4. Load and contribution rate of main components after being spun.

Factor	Factor Load								Contribution Rate of Variances/%	Accumulated Contribution Rate of Variances/%
	Cd	Cr	Hg	Ni	Pb	As	Cu	Zn		
PC1	0.833	0.314	0.204	0.332	0.306	0.198	0.828	0.828	57.2	57.2
PC2	0.168	0.846	−0.080	0.858	0.698	0.923	0.357	0.343	19.3	76.5
PC3	0.136	0.064	0.951	−0.149	0.476	0.060	0.012	0.253	8.1	84.6

As shown in Table 4, component PC1 contributes 57.2% of the total variance. The factor load of Cd, Cu and Zn on PC1 are greater than those of other factors (greater than 0.82), indicating the three heavy metals may come from the same source. In the I_{geo} method, Cd,

Cu and Zn had accumulated to some extent, showing that component PC1 may be affected by human activities. In this area, chemical fertilizer and manure are widely used, and the concentration of Cu and Zn are much higher than others. In Luo and others' [62–65] studies, the pollution of Cu and Zn in the agricultural soil is from manure in agricultural activities, at the same time, as an additive of automobile tires, and the antioxidant in lubricating oil detergent, dust containing the element Zn gets into the soil. The nearest traffic line is only 300 m away from the study area, and the study [66] shows the accumulation of element Zn has much relationship with traffic, with the wear of automobile tires producing dust containing Zn that falls to the topsoil. The coefficient of variation of Cd is second only to Hg. In Tianjin, the background value of element Cd is 0.09 $mg \cdot kg^{-1}$, while the mean value is 0.23 $mg \cdot kg^{-1}$ in the study area, the maximum value is 0.84 $mg \cdot kg^{-1}$, and the concentration of Cd has strong variability and significant difference in spatial distribution. In China, only 30% of Cd in pesticide is absorbed, the other 70% easily produces element enrichment when it is lost to the soil [65]. Above all, the elements Cd, Cu and Zn were affected by the mixed sources of agricultural activity and traffic pollution.

Component PC2 contributes 19.3% of the total variance, the factor load of Cr, Ni, and As on PC2 are all greater than 0.84, while that of Pb is 0.698, showing the four heavy metals may come from the same source. The contribution rate of variances of the four elements ranges from 0.12 to 0.23, belonging to low degree to moderate degree variation; at the same time, the I_{geo} values of the four factors are at an unpolluted level, showing that the impact of external pollution is very small. In some studies, the strong correlation between Cr and Ni has something to do with parent material or a soil-forming process. Above all, the factors Cr, Ni, Pb and As are related to the natural superposition process of alluvial parent material in the plain area, so the source of them is natural source.

The load of element Hg in component PC3 is 0.951, and the coefficient of variation is the highest, showing the highest intensity of external pollution received. The study [64] shows the pollution of Hg by human activities is from particle migration of coal and oil combustion, accumulating in the soil with atmospheric sedimentation. There are many residential housings and industrial enterprises in the study area, and Yangliuqing power plant is also located in the area, so the component PC3 is regarded as the coal combustion source.

3.5. APCS–MLR Model

In the ACPS-MLR model, all the fitting coefficients (R^2) are greater than 0.75, indicating the APCS–MLR model has a high fitting degree with high reliability [67,68], as shown in Figure 4. There are three main absolute principal components (PC1~PC3) and one unrecognized source. The contribution rates of elements Cd, Cu and Zn are 60.0%, 71.8%, and 62.6%, respectively, in source 1, which are higher than others' and corresponds to PC1 (mixed source of agriculture and transportation). The contribution rates of elements Cr, Ni, Pb and As are 71.3%, 55.4%, 81.1%, and 64.3%, respectively, in source 2, and corresponds to PC2 (natural source). The contribution rate of element Hg is 37.7% in source 3, and corresponds to PC3 (coal combustion source). Meanwhile, PC1 and the unrecognized source have a certain degree of influence on the element Hg, and their contribution rates are 33.5% and 26.4%, respectively. The contribution rates using the APCS–MLR model were shown in Figure 4, and the proportion of mixed source is 37.3%, while the natural source, coal combustion source, and unrecognized source are 45.3%, 11.1%, and 5.6%, respectively.

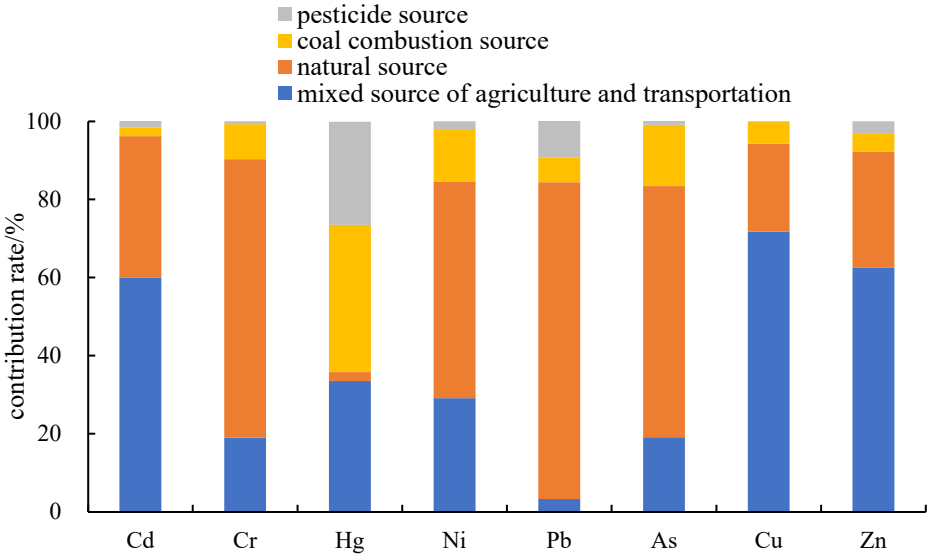


Figure 4. Source contribution ratios of heavy metals in soil based on APCS–MLR model.

3.6. PMF Analysis

The probabilistic matrix factorization (PMF) model is used to further analyze the quantitative sources of eight elements. The concentration and uncertainty of heavy metals were imported into the model. The factor number ranges from 2 to 6, and the number of operations is 20. The initial point is randomly chosen in the PMF model. The reduced value of Q_{Robust}/Q_{exp} is the smallest when the factor varies from 4 to 5, indicating that factor 4 is the optimal choice. Q_{robust} = 675.2, Q_{true} = 789.8 and the ratio is the smallest in this model when the number of factors is 4, and the residual range from −3 to 3 and were in a normal distribution, showing the results have good stability. The fitting coefficient (R^2) of the actual and predictive values of Cr, Cu, Pb, and As are all higher than 0.8, and those of Cd, Ni, Zn, and Hg are all higher than 0.9, indicating the PMF model can fit the information of the original data well.

The four factors in the PMF model represent four different sources of heavy metals. Figure 5 is the factor profiles and source contributions of eight heavy metals based on the PMF in the study area. The contribution rate of Cr, Ni, Pb, and As are higher than others' on factor 1, which corresponds to nature source of PC2.

The contribution rate of Cd is the highest on factor 2, and the contribution rate of Hg is the highest on factor 3. These correspond to coal combustion source of PC3. The contribution rates of Cu and Zn are higher than others' on factor 4.

The PMF model can analyze two factors (factor 2 and factor 4), and the results of this model are almost the same as that of principal component analysis (PC1), so factor 2 can be regarded as pesticide source and factor 4 can be regarded as mixed source of agriculture and transportation.

In the PMF model, the contribution rate of nature source is 24.4%, pesticide source is 23.3%, coal combustion source is 15.1%, and mixed source of agriculture and transportation is 37.3%. The total contribution rate of element Cd (pesticide source) and Hg (coal combustion) is 38.4%, and Cd and Hg are important elements in the study of agricultural soil pollution.

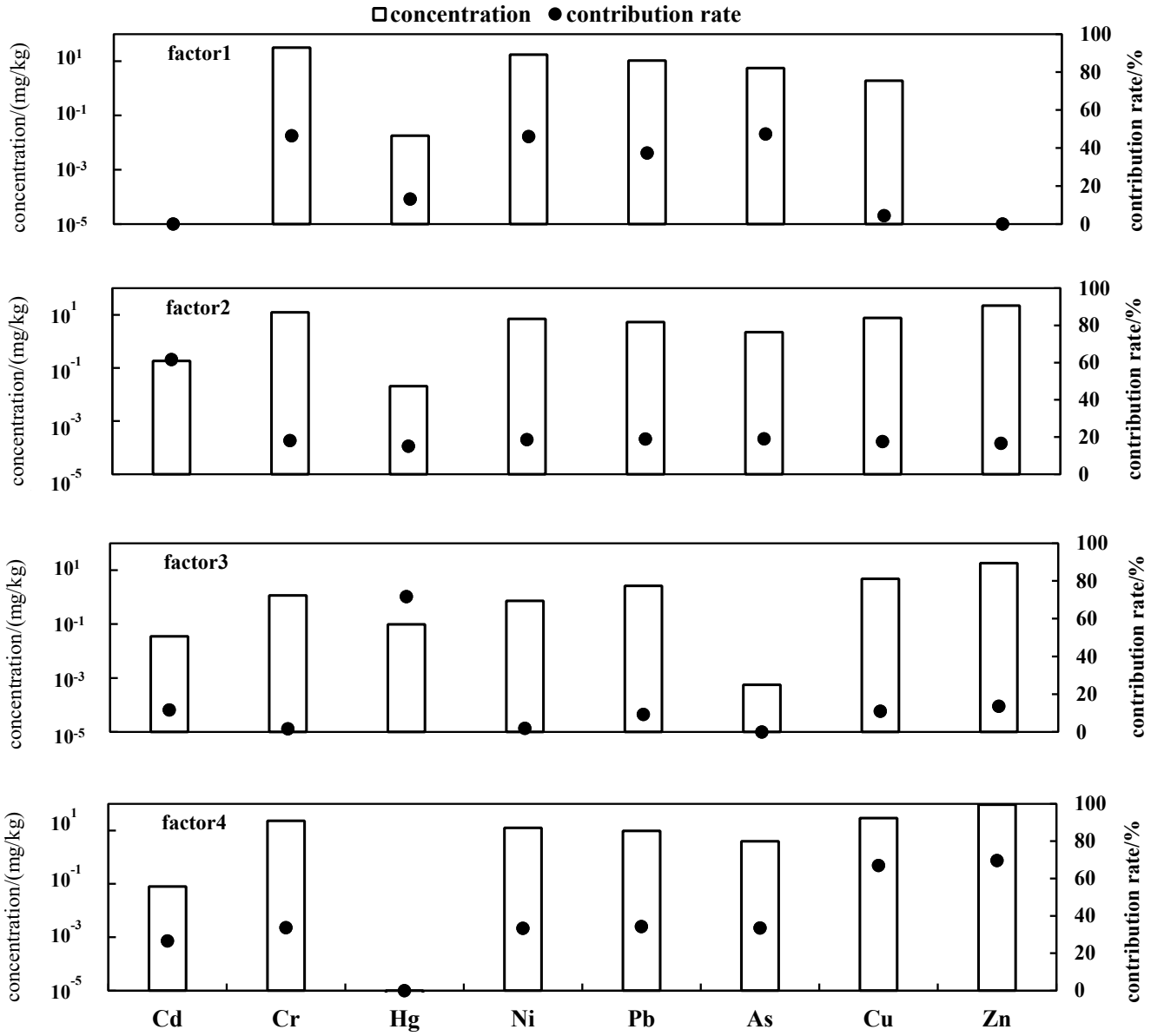


Figure 5. Factor profiles and source contributions of eight heavy metals based on PMF in the study area.

3.7. Comparison of APCS–MLR Model and PMF Model

R^2 is used to assess the fitting degree between the predicted and actual values. When R^2 is close to 1, the predicted and actual value match well in linear regression analysis. Table 5 shows the values of the APCS–MLR and PMF models; the values of the PMF model are higher than those of the APCS–MLR model, indicating the PMF model is more appropriate for the analysis of heavy metal sources in the study area. And in the study [69], PMF performs better than APCS–MLR.

Table 5. The R^2 of APCS–MLR and PMF method.

R^2	Cd	Cr	Hg	Ni	Pb	As	Cu	Zn
APCS–MLR	0.726	0.809	0.95	0.861	0.797	0.889	0.804	0.86
PMF	0.704	0.826	1.000	0.902	0.877	0.911	0.935	0.953

The results of the PMF source analysis perform well when the factor number is 4. The elements Cr, Ni, Pb, and As come from nature source, Cd comes from pesticide source, Hg comes from coal combustion source, Cu and Zn come from mixed source of agriculture and transportation. The APCS–MLR model only has three sources, and the pesticide source is included in mixed source of agriculture and transportation. The APCS–MLR model can't make uncertain estimates and provide an error range before eigenvalue analysis. The results of the PMF model are more reliable by using uncertainty values to weight data [70]. Thus, compared with the APCS–MLR model, the PMF model can accurately analyze the sources of heavy metals in the study area.

3.8. Health Risk Assessment of Heavy Metals in Soil Based on PMF Model

Based on the results of the PMF model, Figure 6 shows the standardization contribution rate of soil heavy metal point source.

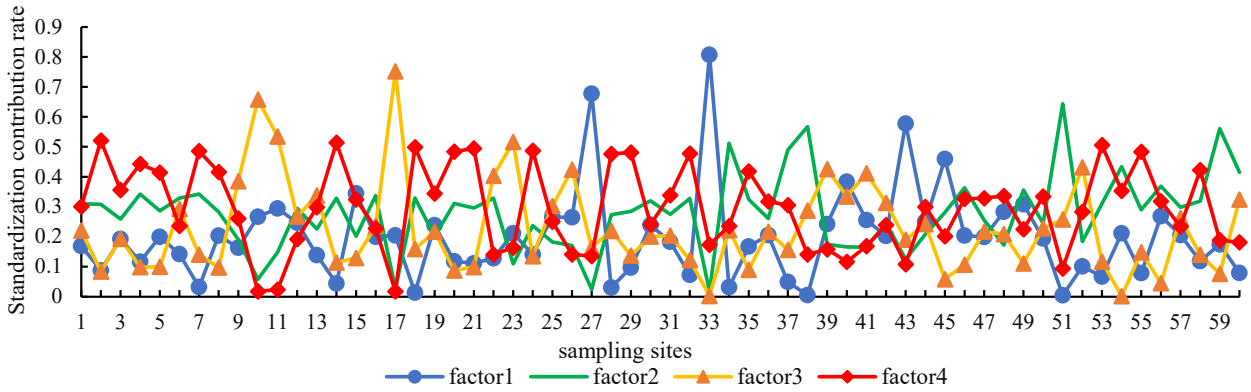


Figure 6. Standardization contribution rate of soil heavy metal point source based on PMF.

The results of the traditional health risk assessment of *HQ*, *HI*, *TCR* (children and adults) in soil are shown in Table 6. In different exposure pathways, $HQ_{ing} > HQ_{der} > HQ_{inh}$. The *HQ* average values of eight heavy metals are sorted by As > Cr > Pb > Ni > Cu > Hg > Zn > Cd, and the values of *HI* for children and adults are all less than 1, indicating the absence of significant non-carcinogenic health risks. The values of *TCR* for adults and children are 2.43×10^{-5} and 1.90×10^{-4}, respectively, and the value for children is greater than 1×10^{-4}, showing the presence of a comprehensive carcinogenic risk caused by heavy metals in the region. The *TCR* average values are sorted by As > Cd > Cr > Ni. The *CR* values of Cr and Ni for adults and children are all less than 1×10^{-6}, indicating the absence of carcinogenic risk. The *CR* values of Cd for adults and children and As for adults are all between 1×10^{-6} and 1×10^{-4}, which means the carcinogenic risk is within an acceptable range. The *CR* value of As for children is greater than 1×10^{-4}, indicating the probability of carcinogenic risk is mainly caused by As.

The non-carcinogenic risk values are different with the different pollution sources of heavy metal in soils. The contribution rate of heavy metal point source was combined with the risk assessment parameters in the PMF model to estimate the non-carcinogenic risk of heavy metals from each pollution source, and the results are shown in Table 7. Figure 7 shows the spatial distribution of eight heavy metals in the surface soil of the study area by using the kriging interpolation method.

Table 6. Results of human health risk assessment for soil heavy metals.

Recipient	Exposure Pathways	Cd	Cr	Hg	Ni	Pb	As	Cu	Zn	*HQ*	*HI* (*TCR*)
children	HQ_{ing}	2.48×10^{-3}	2.44×10^{-1}	7.75×10^{-3}	1.81×10^{-2}	8.41×10^{-2}	3.88×10^{-1}	9.88×10^{-3}	4.05×10^{-3}	7.58×10^{-1}	
	HQ_{inh}	4.57×10^{-8}	4.71×10^{-4}	2.85×10^{-6}	3.22×10^{-7}	1.54×10^{-6}	1.74×10^{-5}	1.81×10^{-7}	7.44×10^{-8}	4.93×10^{-4}	7.81×10^{-1}
	HQ_{der}	4.12×10^{-4}	2.03×10^{-2}	4.49×10^{-5}	1.11×10^{-4}	9.36×10^{-4}	6.44×10^{-4}	5.47×10^{-5}	3.36×10^{-5}	2.25×10^{-2}	
	CR_{ing}	1.52×10^{-5}					1.74×10^{-4}				
	CR_{inh}	8.22×10^{-14}	5.65×10^{-7}		5.58×10^{-9}		9.19×10^{-12}				1.90×10^{-4}
	CR_{der}	2.52×10^{-8}					2.90×10^{-7}				
adults	HQ_{ing}	3.11×10^{-4}	3.05×10^{-2}	9.68×10^{-4}	2.26×10^{-3}	1.05×10^{-2}	4.85×10^{-2}	1.23×10^{-3}	5.06×10^{-4}	9.48×10^{-2}	
	HQ_{inh}	4.57×10^{-8}	4.71×10^{-4}	2.85×10^{-6}	3.22×10^{-7}	1.54×10^{-6}	1.74×10^{-5}	1.81×10^{-7}	7.44×10^{-8}	4.93×10^{-4}	1.00×10^{-1}
	HQ_{der}	9.45×10^{-5}	4.64×10^{-3}	1.03×10^{-5}	2.54×10^{-5}	2.15×10^{-4}	1.48×10^{-4}	1.25×10^{-5}	7.71×10^{-6}	5.16×10^{-3}	
	CR_{ing}	1.89×10^{-6}					2.18×10^{-5}				
	CR_{inh}	8.22×10^{-14}	5.65×10^{-7}		5.58×10^{-9}		9.19×10^{-12}				2.43×10^{-5}
	CR_{der}	5.77×10^{-9}					6.64×10^{-8}				

Table 7. Estimation of non-carcinogenic risk of heavy metals from each pollution source.

Risk Category	Heavy Metal	Children					Adults				
		Factor 1	Factor 2	Factor 3	Factor 4	Sum	Factor 1	Factor 2	Factor 3	Factor 4	Sum
non carcinogenicrisk	Cd	2.38×10^{-7}	1.08×10^{-2}	4.75×10^{-3}	4.39×10^{-4}	1.60×10^{-2}	3.05×10^{-8}	1.38×10^{-3}	6.08×10^{-4}	5.63×10^{-5}	2.04×10^{-3}
	Cr	7.55×10^{-2}	2.95×10^{-2}	2.75×10^{-3}	5.47×10^{-2}	1.62×10^{-1}	9.67×10^{-3}	3.78×10^{-3}	3.52×10^{-4}	7.00×10^{-3}	2.08×10^{-2}
	Hg	4.28×10^{-5}	4.92×10^{-5}	2.33×10^{-4}	2.38×10^{-7}	3.25×10^{-4}	5.48×10^{-6}	6.30×10^{-6}	2.98×10^{-5}	3.05×10^{-8}	4.16×10^{-5}
	Ni	4.12×10^{-2}	1.66×10^{-2}	1.72×10^{-3}	2.98×10^{-2}	8.93×10^{-2}	5.27×10^{-3}	2.13×10^{-3}	2.20×10^{-4}	3.81×10^{-3}	1.14×10^{-2}
	Pb	2.51×10^{-2}	1.27×10^{-2}	6.23×10^{-3}	2.30×10^{-2}	6.70×10^{-2}	3.21×10^{-3}	1.63×10^{-3}	7.98×10^{-4}	2.95×10^{-3}	8.59×10^{-3}
	As	1.32×10^{-2}	5.31×10^{-3}	1.33×10^{-6}	9.36×10^{-3}	2.79×10^{-2}	1.69×10^{-3}	6.79×10^{-4}	1.70×10^{-7}	1.20×10^{-3}	3.57×10^{-3}
	Cu	4.51×10^{-3}	1.82×10^{-2}	1.13×10^{-2}	6.91×10^{-2}	1.03×10^{-1}	5.78×10^{-4}	2.33×10^{-3}	1.45×10^{-3}	8.85×10^{-3}	1.32×10^{-2}
	Zn	2.38×10^{-7}	5.26×10^{-2}	4.29×10^{-2}	2.19×10^{-1}	3.15×10^{-1}	3.05×10^{-8}	6.73×10^{-3}	5.49×10^{-3}	2.81×10^{-2}	4.03×10^{-2}
	HI	1.60×10^{-1}	1.46×10^{-1}	6.99×10^{-2}	4.05×10^{-1}	7.81×10^{-1}	2.04×10^{-2}	1.87×10^{-2}	8.95×10^{-3}	5.20×10^{-2}	1.00×10^{-1}
carcinogenicrisk	Cd	1.53×10^{-10}	2.83×10^{-7}	3.06×10^{-6}	6.96×10^{-6}	1.03×10^{-5}	1.96×10^{-11}	3.62×10^{-8}	3.91×10^{-7}	8.89×10^{-7}	1.32×10^{-6}
	Cr	4.87×10^{-5}	1.90×10^{-5}	1.77×10^{-6}	3.52×10^{-5}	1.05×10^{-4}	6.22×10^{-6}	2.43×10^{-6}	2.26×10^{-7}	4.50×10^{-6}	1.34×10^{-5}
	Ni	2.65×10^{-5}	1.07×10^{-5}	1.11×10^{-6}	1.92×10^{-5}	5.75×10^{-5}	3.39×10^{-6}	1.37×10^{-6}	1.41×10^{-7}	2.45×10^{-6}	7.35×10^{-6}
	As	8.51×10^{-6}	3.42×10^{-6}	8.54×10^{-10}	6.03×10^{-6}	1.80×10^{-5}	1.09×10^{-6}	4.37×10^{-7}	1.09×10^{-10}	7.71×10^{-7}	2.3×10^{-6}
	TCR	8.37×10^{-5}	3.34×10^{-5}	5.94×10^{-6}	6.74×10^{-5}	1.90×10^{-4}	1.07×10^{-5}	4.27×10^{-6}	7.59×10^{-7}	8.62×10^{-6}	2.43×10^{-5}

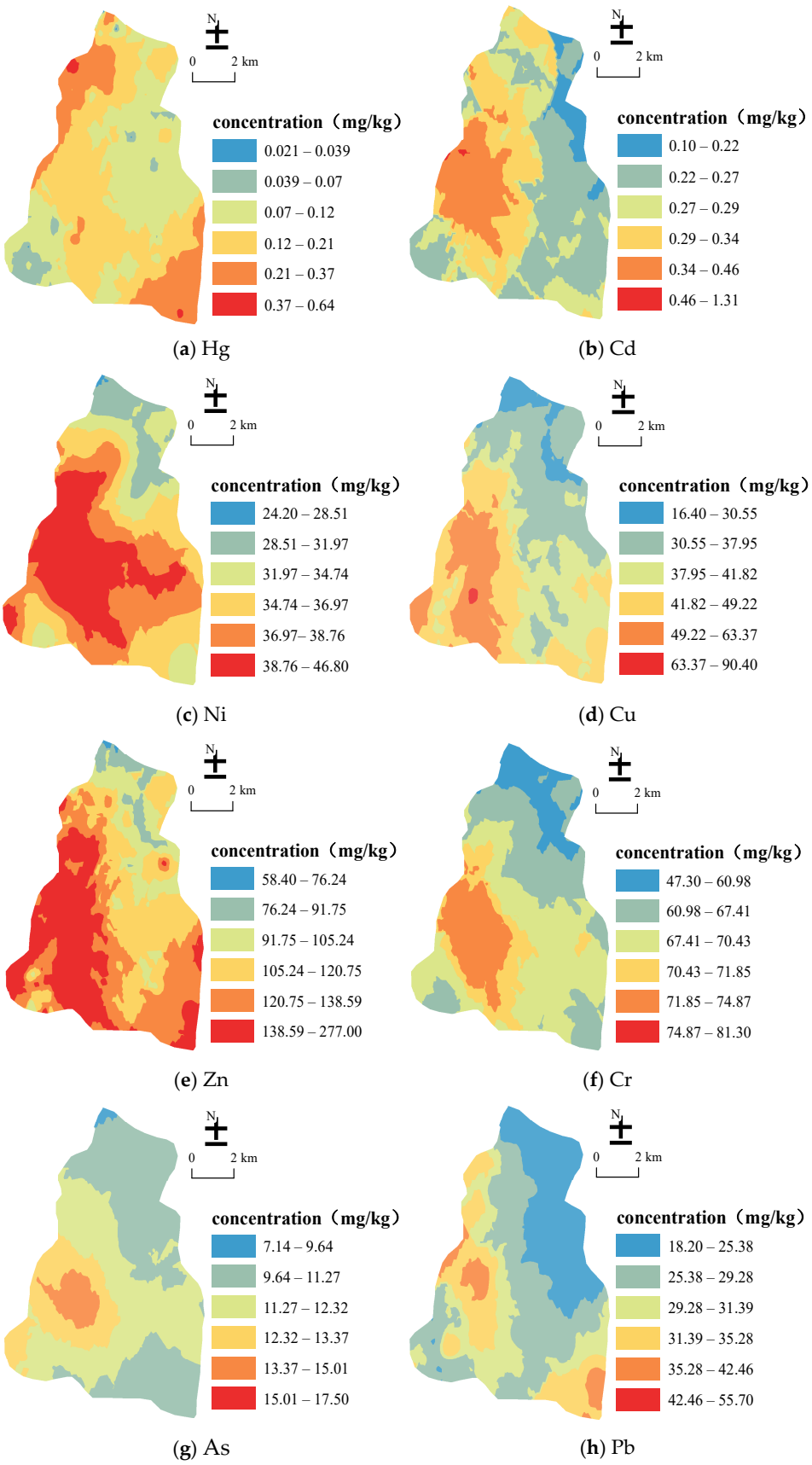


Figure 7. Spatial distribution of eight heavy metals in the surface soil of the study area.

The *TCR* values of different pollution sources are as follows: natural source (children 8.37×10^{-5}, adults 1.07×10^{-5}), mixed source (children 6.74×10^{-5}, adults 8.62×10^{-6}),

pesticide source (children 3.34×10^{-5}, adults 4.27×10^{-6}), coal combustion source (children 5.94×10^{-6} adults 7.59×10^{-7}). The value of *TCR* in natural source is the highest. In natural source (F1), the element Cr is the main contributor of *HI* (7.55×10^{-2}) and *TCR* (4.87×10^{-5}) for children. The eight heavy metals in the surface soil of the study area present the distribution characteristics of block shaped regions gradually increasing in value from the north to the southwest (Figure 7f). For element Cd, pesticide source (F2, 1.08×10^{-2}) and mixed source (F4, 6.96×10^{-6}) contribute much more than others of *HI* and *TCR* respectively for children. There is a significant difference between the eastern and western regions (Figure 7b). The western region of the Ziya River distributes obvious successive high-value areas, and in the eastern region, low-value and mid-value blocks appear with mixed distribution. Vegetable greenhouse planting demonstration areas are located in the western region, and the use of mulch film, fertilizers and pesticides may lead to non-carcinogenic health risk for residents. For the element Hg, coal combustion (F3) contributes much more than others of *HI*, the value is 2.33×10^{-4} (for children) and 2.98×10^{-5} (for adults), respectively. High-value areas are distributed in the northwest and southeast regions, while the low-value and mid-value are in the middle (Figure 7a). This feature is closely related to the increase of Hg concentration caused by human activities. The high-value region is near to the industrial area, which includes the chemical and metal products, packaging, and textile enterprises, and these enterprises discharge waste gas and coal waste gas that may contribute a large amount of heavy metals and pose a threat to local residents. The *HI* of Cu and Zn come from the mixed source of agriculture and transportation (F4), and the values for children are 6.91×10^{-2} and 0.219, respectively, for adults are 8.85×10^{-3} and 2.81×10^{-2}, respectively. In Figure 7, the high-value area focuses on the southwest and southeast regions, and the high-value area of element Cu (49.22~90.40 mg/kg) occupies 36.7%, and Zn (120.75~277.00 mg/kg) occupies 55.0%. The two high-value belts along the Beijing Shanghai Expressway and in the direction of Dashawo Village and Wangjia Village, and the organic fertilizers in the residential area and the dust from the expressway may cause non-carcinogenic risk for the residents.

This study does have limitations, and heavy metals in agricultural products were not analyzed. Agricultural products, soil, and humans were not uniformly assessed for risk. Future work should clarify the potential transfer model between farmland soil, agricultural products, and humans. In the following work, soil samples from different depths can be collected for further analysis, and heavy metal analysis can be conducted on various crops planted (such as wheat, rice, vegetables, etc.) to further clarify the pathways of their impact on risks to human health. This is more conducive to the classification and control of agricultural land, thereby avoiding the impact of heavy metals on human health.

4. Conclusions

(1) Cd and Hg pollution were the most severe among the eight heavy metals in the study aera, with the average values exceeding the background by 151.9% and 324.1%, respectively. About 15% of the sites were at moderate to severe pollution levels. The geo-accumulation index average value of element Zn is 0.15 belonging to minor pollution level and the I_{geo} average values of the other elements belong to no pollution level.

(2) The results of correlation analysis, PCA, APCS–MLR, and PMF showed the sources of heavy metals in the study area are natural sources, mixed sources of agriculture and transportation, coal combustion sources, and pesticide sources. Compared with APCS–MLR, the PMF model is more appropriate for the analysis of heavy metal sources in the study area. The elements Cr, Ni, Pb, and As mainly come from natural source with the proportion of 24.4%; the element Cd mainly comes from pesticide

source with the proportion of 23.3%; the element Hg mainly comes from coal combustion source with the proportion of 15.1%; the elements Cu and Zn mainly come from mixed source of agriculture and transportation with the proportion of 37.3%.

(3) The health risk assessment model shows the *HI* values of heavy metals for children and adults are 0.781 and 0.100, respectively, which means the absence of obvious non-carcinogenic risk in the three pathways: ingestion of crops, hand-to-mouth ingestion, skin contact, and the *HI* values of all elements are sorted by As > Cr > Pb > Ni > Cu > Hg > Zn > Cd. The *TCR* values for adults and children are 2.43×10^{-5} and 1.90×10^{-4}, respectively, which means the total carcinogenic risk is caused by heavy metals. The *CR* value of As for children is more than 1×10^{-4}, indicating the carcinogenic risk in this region is mainly caused by element As.

(4) The results of the PMF model show the *TCR* value of natural source is the highest, with Cr being the main contributor to the childhood maximum total non-carcinogenic risk indices (*HI*) and childhood *TCR* in the source contribution. The HI value in the pesticide source (1.08×10^{-2}) and the TCR value in the mixed source (6.96×10^{-6}) of the element Cr are more significant than others. Hg contributes the most to coal combustion sources, and the contribution of HI (Cu, Zn) is in the mixed source of agriculture and transportation.

Environmental sustainability is becoming more and more important, and future efforts could integrate soil heavy metal research with environmental management and pollution control.

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References

1. Liu, Q.; Wang, S.; Zhou, J.; Bao, L.; Zhou, W.; Zhang, N. Accumulation and Transport of Cd, Pb, As, and Cr in Different Maize Varieties in Southwest China. *Agriculture* **2025**, *15*, 203. [CrossRef]
2. Wang, Y.; Xin, C.; Yu, S.; Xue, H.; Zeng, P.; Sun, P.; Liu, F. Evaluation of Heavy Metal Content, Sources, and Potential Ecological Risks in Soils of Southern Hilly Areas. *Environ. Sci.* **2022**, *43*, 4756–4766.
3. Jiang, H.; Cai, L.; Wen, H.; Hu, G.; Chen, L.; Luo, J. An integrated approach to quantifying ecological and human health risks from different sources of soil heavy metals. *Sci. Total Environ.* **2020**, *701*, 134466. [CrossRef]
4. Zhao, Z.; Zhao, Z.; Fu, B.; Wu, D.; Wang, J.; Li, Y.; Tang, W. Distribution and fractionation of potentially toxic metals under different land-use patterns in suburban areas. *Pol. J. Environ. Stud.* **2022**, *31*, 475–483. [CrossRef] [PubMed]
5. Yi, X.; Xie, Z.; Wang, W.; Luo, X.; Shen, L.; Liu, B.; Shao, L. Source apportionment of heavy metals in soil of Guangzhou: Comparison of three receptor models. *J. China Univ. Sci. Technol.* **2021**, *51*, 813–821.
6. Tian, X.; He, G.; Luo, L.; Wu, Y.; Cui, W. Spatial distribution characteristics and source apportionment of heavy metals in vineyard soil at east piedmont of Helan Mountains. *Southwest Agric. Sci.* **2021**, *34*, 641–646.
7. Cai, Z.; Yang, X. Research on Restoration of Heavy Metal Contaminated Farmland Based on Restoration Ecological Compensation Mechanism. *Sustainability* **2023**, *15*, 5201. [CrossRef]
8. Li, Q.; Han, Z.; Tian, Y.; Xiao, H.; Yang, M. Risk Assessment of Heavy Metal in Farmlands and Crops Near Pb-Zn Mine Tailing Ponds in Niujiaotang, China. *Toxics* **2023**, *11*, 106. [CrossRef]

9. Ma, J.; Ge, M.; Wang, S.; Deng, L.; Sun, J.; Jiang, Y.; Zhou, L. Health Risk Assessment and Priority Control Factors Analysis of Heavy Metals in Agricultural Soils Based on Source-oriented. *Environ. Sci.* **2024**, *45*, 396–406.
10. Zhang, S. Assessment of soil heavy metal pollution and health risk in different functional areas of Shanghai City based on GIS. *J. Environ. Eng. Technol.* **2022**, *12*, 1226–1236.
11. Yu, L.; Wang, F.; Fan, H.; Kang, G.; Liu, H.; Wang, D.; Xu, J. Spatial distribution, source apportionment, and ecological risk assessment of soil heavy metals in Jianghugongmi Producing Area, Shandong Province. *Environ. Sci.* **2022**, *43*, 4199–4211.
12. Che, K.; Chen, C.; Zheng, Q.; Fan, H.; Wei, M.; Luo, P.; Yu, J. Characteristics and health risks in surrounding soils heavy metal emissions from coal-fired power plants and heavy metal pollution. *Environ. Sci.* **2022**, *43*, 4578–4589.
13. Qiao, W.; Wang, Y.; Zhang, D.; Yin, X.; Bai, G.; He, P. Identification of heavy metal distribution and sources in soil from a mining area. *Geoscience* **2022**, *36*, 543–551.
14. Guo, H.; Sun, Y.; Wang, X.; Zhang, L.; Mei, Y.; Liu, Q.; Wang, Q. Spatial distribution characteristics and source analysis of soil heavy metals in county-level city. *Acta Sci. Circumstantiae* **2022**, *42*, 287–297.
15. Zhang, H.; Wu, C.; Gong, J.; Yuan, X.; Wang, Q.; Pei, W.; Long, T.; Qiu, J.; Zhang, H. Assessment of heavy metal contamination in roadside soils along the Shenyang-Dalian Highway in Liaoning Province, China. *Pol. J. Environ. Stud.* **2017**, *26*, 1539–1549.
16. Zhang, R.; Chen, T.; Pu, L.; Qie, L.; Huang, S.; Chen, D. Current Situation of Agricultural Soil Pollution in Jiangsu Province: A Meta-Analysis. *Land* **2023**, *12*, 455. [CrossRef]
17. Ning, Y.; Yang, B.; Yang, S.; Ye, J.; Li, J.; Ren, L.; Liu, Z.; Bi, X.; Liu, J. Application of Pb Isotopes and REY Patterns in Tracing Heavy Metals in Farmland Soils from the UpperMiddle Area of Yangtze River. *Int. J. Environ. Res. Public Health* **2023**, *20*, 966. [CrossRef]
18. Wu, Y.; Xia, Y.; Mu, L.; Liu, W.; Wang, Q.; Su, T.; Yang, Q.; Milinga, A.; Zhang, Y. Health Risk Assessment of Heavy Metals in Agricultural Soils Based on Multi-Receptor Modeling Combined with Monte Carlo Simulation. *Toxics* **2024**, *12*, 643. [CrossRef]
19. Shen, G.; Ru, X.; Gu, Y.; Liu, W.; Wang, K.; Li, B.; Guo, Y.; Han, J. Pollution Characteristics, Spatial Distribution, and Evaluation of Heavy Metal(loid)s in Farmland Soils in a Typical Mountainous Hilly Area in China. *Foods* **2023**, *12*, 681. [CrossRef]
20. Zhang, J.; Liu, Y.; Hong, S.; Wen, M.; Zheng, C.; Liu, P. Speciation Analysis and Pollution Assessment of Heavy Metals in Farmland Soil of a Typical Mining Area: A Case Study of Dachang Tin Polymetallic Ore, Guangxi. *Appl. Sci.* **2023**, *13*, 708. [CrossRef]
21. Ma, J.; She, Z.; Wang, S.; Deng, L.; Liu, P.; Sun, J. Health Risk Assessment of Heavy Metals in Agricultural Soils Around the Gangue Heap of Coal Mine Based on Monte Carlo Simulation. *Environ. Sci.* **2023**, *44*, 5666–5678.
22. Yin, F.; Feng, K.; Yin, C.; Bai, D.; Wang, R.; Zhou, Y.; Liang, Y.; Liu, L. Evaluation and source analysis of heavy metal in cultivated soil around typical industrial district of Qinghai province. *China Environ. Sci.* **2021**, *41*, 5217–5226.
23. Zhang, H.; Cui, W.; Huang, Y.; Li, Y.; Zhong, X.; Wang, L. Evaluation and source analysis of heavy metal pollution of farmland soil around the mining area of karst region of central Guizhou Province. *Acta Sci. Circumstantiae* **2022**, *42*, 412–421.
24. Chen, J.; Fang, H.; Wu, J.; Lin, J.; Lan, W.; Chen, J. Distribution and source apportionment of heavy metals in farmland soils using PMF and lead isotopic Composition. *J. Agro-Environ. Sci.* **2019**, *38*, 1026–1035.
25. Xia, Z.; Bai, Y.; Wang, Y.; Gao, X.; Ruan, X.; Zhong, Y. Spatial distribution and source analysis of soil heavy metals in a small watershed in the mountainous area of southern Ningxia based on PMF model. *Environ. Sci.* **2022**, *43*, 432–441.
26. Song, Q.; Xu, X.; Wu, Q.; Yang, H.; Wang, C.; Gu, Z.; Xu, M. Quantitative analysis of environmental risk of heavy metal sources in soil based on PMF model. *J. Nat. Sci. Hunan Norm. Univ.* **2022**, *45*, 76–83.
27. Zheng, Y.; Wen, H.; Cai, L.; Luo, J.; Tang, D.; Wu, M.; Li, H.; Li, D. Source analysis and risk assessment of heavy metals in soil of county scale based on PMF model. *Environ. Sci.* **2023**, *44*, 5242–5252.
28. Yang, D.; Yang, Y.; Hua, Y. Source Analysis Based on the Positive Matrix Factorization Models and Risk Assessment of Heavy Metals in Agricultural Soil. *Sustainability* **2023**, *15*, 13225. [CrossRef]
29. Chen, H.; Sun, X.; Sun, L.; An, Y.; Xiao, Y.; Zhang, J.; Hong, Y.; Song, X. A Comprehensive Study of Spatial Distribution, Pollution Risk Assessment, and Source Apportionment of Topsoil Heavy Metals and Arsenic. *Land* **2024**, *13*, 2151. [CrossRef]
30. Zhang, C.; Wang, Z.; Liu, L.; Liu, Y. Source Analysis of Soil Heavy Metals in Agricultural band Around the Mining AreaBased on APCS-MLR Receptor Model and Geostatistical Method. *Environ. Sci.* **2023**, *44*, 3500–3508.
31. Hu, Z.; Wu, Z.; Luo, W.; Xie, Y. Content, Sources, and Ecological Risk Assessment of Heavy Metals in Soil of Typical Karst County. *Environ. Sci.* **2024**, *45*, 5507–5516.
32. Li, J.; Gao, Z.; Ma, L.; Ma, J.; Zhang, M.; Ma, X.; Zang, F.; Li, X. Multiproxy Comprehensive Analysis for Source Apportionment and Pollution of Heavy Metals in Upban Drinkingwater Source Soils from the Lanzhou Reach of the Yellow River. *Environ. Sci.* **2024**, *45*, 6723–6733.
33. Li, W.; Zhou, X.; Wang, B.; Ding, D.; Wu, D.; Zhang, Z. Pollution characteristics and assessment of heavy metal in different land-use types in Tianjin City. *Bull. Soil. Water Conserv.* **2018**, *38*, 200–205.
34. Ji, D.; Zeng, W.; Zhang, X.; Zhang, J.; Wang, Q.; Zhang, W.; Deng, L.; Yang, G.; Wu, S. Ecological risk assessment and principal component analysis of heavy metals in suburban farmland soils of Tianjin. *Environ. Chem.* **2019**, *38*, 1955–1965.

35. Wang, B.; Zhang, Z. The features and potential ecological risk assessment of soil heavy metals in Tianjin suburban farmland. *Environ. Monit. China* **2012**, *28*, 23–27.
36. Xie, W.; Yang, Y.; Hou, J. Characteristics of selenium and heavy metals concentrations in soils and vegetables and screening of green selenium-enriched vegetables in a base of Tianjin. *Environ. Chem.* **2018**, *37*, 2790–2799.
37. Zhang, Y.; Han, J.; Tu, Q.; Yang, Y.; Xu, Y.; Shi, R. Accumulation Characteristics and Evaluation of Heavy Metals in Suburban Farmland Soils of Tianjin. *J. Ecol. Rural. Environ.* **2019**, *35*, 1445–1452.
38. Peng, H.; Ma, J.; Ma, Y.; Chen, Y. Characteristics and source identification of heavy metal pollution in agricultural soils and vegetables in Wuqing District, Tianjin City, China. *Chin. J. Ecol.* **2019**, *38*, 2102–2112.
39. Chen, H.; Teng, Y.; Lu, S.; Wang, Y.; Wu, J.; Wang, J. Source apportionment and health risk assessment of trace metals in surface soils of Beijing metropolitan, China. *Chemosphere* **2016**, *144*, 1002–1011. [CrossRef]
40. Zhang, H.; Wang, Y.; Wang, H.; Ju, W.; Huang, R.; Liu, R.; Du, M. Heavy metal pollution characteristics and health risk assessment of soil from an abandoned site for lead smelting of waste lead batteries. *J. Environ. Eng. Technol.* **2023**, *13*, 769–777.
41. Cheng, R. Pollution characteristics and health risk assessment of heavy metals in farmland soil downstream of a copper mine slag dumps. *J. Environ. Eng. Technol.* **2020**, *10*, 280–287.
42. Wang, H.; Wu, J.; Tian, Z.; Li, Y.; Gong, B. Status and development trend of soil pollutant health risk assessment technology. *J. Environ. Eng. Technol.* **2023**, *13*, 778–784.
43. Zhao, X.; Duan, L.; Zhou, J.; Liu, X.; Lu, W.; Qiu, J.; Ke, H.; Zheng, H. Distribution characteristics, source analysis and risk assessment of heavy metals in sediments of Wanghu Lake of Hubei Province. *J. Environ. Eng. Technol.* **2023**, *13*, 1021–1030.
44. Lv, Y.; Wang, Q.; Sun, X.; Zhang, Z.; Zhang, Y.; Gao, Y. Pollution characteristics and source identification of heavy metals in farmland soils around a tailing pond in Zhejiang Province. *J. Environ. Eng. Technol.* **2023**, *13*, 1464–1475.
45. U.S. EPA. *Method 6010D (SW-846): Inductively Coupled Plasma-Atomic Emission Spectrometry*; Revision 4; U.S. EPA: Washington, DC, USA, 2014.
46. Ministry of Ecology and Environment of the People's Republic of China. *Soil and Sedimen—Determination of Mercury, Arsenic, Selenium, Bismuth, Antimony—Microwave Dissolution/Atomic Fluorescence Spectrometry*; Ministry of Ecology and Environment of the People's Republic of China: Beijing, China, 2014.
47. Fan, S. Pollution and health risk assessment of heavy metals in soil neighborhoods around a smelter in Changqing town of Baoji city. *Environ. Pollut. Control.* **2015**, *37*, 46–54.
48. Jia, Y.; Zhang, W.; Liu, M.; Peng, Y.; Hao, C. Spatial Distribution, Pollution Characteristics and Source of Heavy Metals in Farmland Soils around Antimony Mine Area, Hunan Province. *Pol. J. Environ. Stud.* **2022**, *31*, 1653–1665. [CrossRef]
49. Tang, Z.; Deng, R.; Zhang, J.; Ren, B.; Hursthouse, A. Regional distribution characteristics and ecological risk assessment of heavy metal pollution of different land use in an antimony mining area-Xikuangshan, China. *Hum. Ecol. Risk Assess.* **2020**, *26*, 1779–1794. [CrossRef]
50. Mohamed, K.; Elsayed, S.; Enas, M.; Sahar, A.; Ali, A.; Rosa, L.; Manal, A. Quantitative Evaluation of Soil Quality Using Principal Component Analysis: The Case Study of El-Fayoum Depression Egypt. *Sustainability* **2021**, *13*, 1824. [CrossRef]
51. Markus, R. What is principal component analysis? *Nat. Biotechnol.* **2008**, *26*, 303–304.
52. Sun, Y.; Zhou, S.; Meng, S.; Wang, M.; Mu, H. Principal component analysis–artifcial neural network-based model for predicting the static strength of seasonally frozen soils. *Sci. Rep.* **2023**, *13*, 16085.
53. Wei, Q.; Jin, L.; Chen, W.; Gu, H. Pollution Characteristics and Source Analysis of Heavy Metals in Sediment of Panlong River. *Shandong Agric. Sci.* **2020**, *52*, 75–82.
54. Gholizadeh, M.; Melesse, A.; Reddi, L. Water quality assessment and apportionment of pollution sources using APCS-MLR and PMF receptor modeling techniques in three major rivers of South Florida. *Sci. Total Environ.* **2016**, *566–567*, 1552–1567. [CrossRef]
55. Xu, J.; Xie, R.; Liu, L.; Huang, Z. Evaluating the Level of Total Mercury Present in the Soils of a Renowned Tea Production Region. *Agronomy* **2025**, *15*, 435. [CrossRef]
56. U.S. EPA. *A Framework for Assessing Health Risk of Environmental Exposures to Children*; U.S. Environmental Protection Agency: Washington, DC, USA, 2006.
57. China National Environmental Monitoring Centre. *Soil Background Values in China*, 1st ed.; China Environmental Science Press: Beijing, China, 1990; pp. 494–496.
58. *GB 15618-2018*; Soil Environmental Quality Risk Control Standard for Soil Contamination of Agricultural Land. Ministry of Ecology and Environment of the People's Republic of China: Beijing, China, 2018.
59. Hu, H.; Gao, L.; Zhang, H.; Zhou, X.; Zheng, J.; Hu, J.; Hu, H.; Ma, Y. Effectiveness of Passivator Amendments and Optimized Fertilization for Ensuring the Food Safety of Rice and Wheat from Cadmium-Contaminated Farmland. *Sustainability* **2022**, *14*, 15026. [CrossRef]
60. Guo, X.; Li, J.; Lin, Z.; Ma, L. The Impact of Environmental Regulation and Technical Cognition on Farmers' Adoption of Safety Agro-Utilization of Heavy Metal-Contaminated Farmland Soil. *Sustainability* **2024**, *16*, 3343. [CrossRef]

61. Dong, L.; Fang, B. Analysis of spatial heterogeneity of soil heavy metals in tea plantation: Case study of high quality tea garden in Jiangsu and Zhejiang. *Geogr. Res.* **2017**, *36*, 391–404.
62. Luo, L.; Ma, Y.; Zhang, S.; Wei, D.; Zhu, Y. An inventory of trace element inputs to agricultural soils in China. *J. Environ. Manag.* **2009**, *90*, 2524–2530. [CrossRef]
63. Li, W.; Cui, Y.; Zeng, C.; Zhu, Y.; Peng, Y.; Wang, K.; Li, S. Pollution characteristics and source analysis of heavy metals in farmland soils in the taige canal valley. *Environ. Sci.* **2019**, *40*, 5073–5081.
64. Ju, T.; Wu, X.; Shi, H.; Gao, F.; Li, X.; Wang, Y.; Luan, T.; Fan, P. Heavy metal pollution and ecological risk assessment of arable land soil in Haigou small watershed. *J. Environ. Eng. Technol.* **2018**, *8*, 556–562.
65. Ai, J.; Wang, N.; Yang, J. Source apportionment of soil heavy metals in Jiapigou goldmine based on the UNMIX model. *Environ. Sci.* **2014**, *35*, 3530–3536.
66. Zhang, J.; Xia, J.; Chen, S.; Wu, Y.; Pang, Y.; Huang, T. Source analysis of heavy metal lead in Luoma Lake sediments based on Pb stable isotopes. *J. Environ. Eng. Technol.* **2023**, *13*, 1011–1020.
67. Yuan, H.; Zhong, H.; Zhao, L.; Ma, C. Analysis of Heavy Metal Pollution Sources of Typical FarmlandSoils in Chongzhou City Based on PCA/APCS Receptor Model. *Sichuan. Environ.* **2019**, *38*, 35–43.
68. Hingorani, R.; Jimeenez, R.; Grande, M.; Castillo, A.; Nevshupa, R.; Castellota, M. From analysis to decision: Revision of a multifactorial model for the in situ assessment of NOx abatement effectiveness of photocatalytic pavements. *Chem. Eng. J.* **2020**, *402*, 126250. [CrossRef]
69. Deng, J.; Zhang, Y.; Qiu, Y.; Zhang, H.; Du, W.; Xu, L.; Hong, Y.; Chen, Y.; Chen, J. Source apportionment of $PM_{2.5}$ at the Lin'an regional background site in China with three receptor models. *Atmos. Res.* **2018**, *202*, 23–32. [CrossRef]
70. Gan, Y.; Huang, X.; Li, S.; Liu, N.; Li, Y.; Freidereich, A.; Wang, W.; Wang, R.; Dai, J. Source quantification and potential risk of mercury, cadmium, arsenic, lead, and chromium in farmland soils of Yellow River Delta. *J. Cleaner Prod.* **2019**, *221*, 98–107. [CrossRef]

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