Analysis and Source Identification of Heavy Metals in Soils of Central Urban Area of Chongqing, China

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heavy metals. The main sources of heavy metals are human activities, such as mineral mining, coal burning, irrigating land with contaminated water and applying impure mineral fertilizers, which are among the pollution sources that increase the content of heavy metals in soil (Wang and Li et al., 2020). Such as: Selinus(2005) found that the continuous mining of metal mines led to a high concentration of cadmium in the plants near the waters in central Sweden. Birke(2017) revealed that industrial activities, urban agglomeration and fertilizer use were responsible for the high local concentrations of heavy metals Cd and Hg in European agricultural soils. These are the point pollution sources or non-point pollution sources that affect the high content of heavy metals.

With the development and progress of industry, people have gradually realized the threat and influence of heavy metals on human body. Scholars began to study heavy metals in the 1980s and 1990s. DeRosa (1991) assessed the effects of lead, an environmental poison, on children's physical or intellectual development. Before 2000, the research focused on the spatial distribution and pollution assessment of heavy metal pollution. With the development of geostatistics, Kriging method and inverse distance weighted interpolation methods have been widely used in the study of spatial distribution. From 2000 to 2010, research focused on heavy metal risk assessment pollution index, spatial variation, biological stimulation, biological monitoring and other aspects. Since 2010, the monitoring of heavy metal pollution sources has become a hot topic. At present, the most widely used source analysis models in the field of soil mainly include APCS/MLR model, PMF model, Unmix model, Isotope ratio method, etc. Due to the differences in soil parent material, climate conditions and human interference, the sources of heavy metals vary greatly, so it is necessary to detect the specific sources of heavy metals in the site. For example, Liu (2021) found that the heavy metals Hg, Cd, Cu, Pb and Zn in agricultural soils of southern Shandong Peninsula in China came from coal burning, agricultural practices, and industrial activities. Aguilera (2021) explained that the main sources of heavy metals Pb, Zn, Cu and Cr in street dust in Mexico City are human activities, possibly due to vehicle traffic. Ivankovic(2010) believed that the heavy metal Ni in the urban soil of Belgrade, Serbia was derived from peridotites and serpentinites, and Pb was derived from traffic activities.

Chongqing is one of the megacities in Chengdu-Chongqing region, an economic and political center in southwest China, a comprehensive transportation hub and the largest industrial and commercial city in the west of China. As a traditional heavy industrial city, industrial pollutant emission, mountainous landscape and humid climate all lead to the increase of heavy metal content in the soil, which in turn affects the health of local residents. There are serious regional haze phenomena in Chongqing and even the whole Sichuan-Chongqing region. Therefore, the investigation and source analysis

of soil heavy metal pollution in this region are of great significance to ensure soil quality and food safety in this region.

The objectives of this study were to: (1) Field sampling and laboratory analysis were conducted in the central urban area of Chongqing to investigate the content of heavy metals in the regional soil. (2) PCA-APCS receptor model was used to analyze the internal relationship between soil heavy metal elements. (3) CATREG was used to analyze the relationship between heavy metals and environmental factors. (4) ArcGIS hotspot analysis was used to analyze the spatial variation of soil heavy metal content. This will provide more information to city planners and decision-makers to help them make decisions, promote the sustainable development and management of Chongqing, and provide them with valuable insights. Supplement analysis of the sources of heavy metal pollution in Sichuan and Chongqing areas, and provide basic data and theoretical support for the early warning and forecast, joint prevention and control of soil pollution.

2. Materials and Methods

2.1 Study area

Chongqing is located in the southwest of mainland China, the upper reaches of the Yangtze River, and the parallel range-valley region in the east of the Sichuan Basin, between 105°01' -110 °11' E and 28°10' -32 °13' N. The topography of Chongqing gradually decreases from south to north to the Yangtze River Valley, with hills and low mountains mainly in the northwest and central part, Daba Mountain in the northeast and Wuling Mountain in the southeast (Deng and Li et al., 2020), Landform to hills, mountain - based, large slope area, known as the "mountain city" (Xu and Wang et al., 2018). The central urban area includes 6 districts of Yuzhong, Jiangbei, Dadukou, Shapingba, Nan'an, Jiulongpo and 3 districts of Banan, Yubei and Beibei in the outer urban circle (Fig.1) .

Fig.1 Study the distribution map of the location and sampling points

2.2 Sample collection and testing

In accordance with the industry technical standards "Specification for Geochemical Assessment of Land Quality" (DZ/T0259-2016) and "Digestion of Total Metal Elements in Soil and Sediments by Microwave Digestion" (HJ832-2017) issued by the Ministry of Environmental Protection, surface soil samples of agricultural land were collected by grid with a sampling density of 4 km and a sampling depth of 40cm. A total of 342 single spot samples of surface soil were collected in three multi-point collection combinations within 100m of the sampling center. Taking the sampling point located by GPS as the center, the four sampling points were determined by radiating 40m to the periphery (Fig.1). When sampling, avoid special areas such as roads and ditches, and take 1kg soil samples according to the method of quartering.

Samples collected in the field are sealed in plastic bottles and sent to the laboratory of Anhui Rock and Mineral Testing Center with national first-class qualification for testing. Laboratory, after receiving the sample soil samples after drying, removing sand, such as plant debris, grinding, agate mortar over 2 mm diameter soil sieve, regrinding all through 100 mesh sieve, among them with one-time grinding all through 100 mesh sieve is the best, with four points method take 200g sample save backup, according to take samples of 4g in the mould with boric acid edge at the bottom, Under the pressure of 40 tons, the holding time is 20s, and the sample with diameter of 32mm and thickness of 4mm is pressed to carry out drift correction experiment. The detection limits of 11 heavy metals, such as As, Cr, Pb, Zn and As, in the samples were calculated using different determination methods⁴. The detection lines were all up to $\text{mg}\cdot\text{kg}^{-1}$, which could meet the rapid analysis requirements of the II type of soil in the national soil environmental quality standard

2.3 PCA/APCS receptor model

The purpose of the principal component is to compress the original several related variables into a few comprehensive variables through linear combination for investigation. Principal component analysis uses dimension-reduction to reveal the hidden relationship between variables and classifies elements according to correlations to judge the source of elements in each factor (Dong and Jia et al., 2018). However, it can only give the major contributing factors of each source in a qualitative way to explore the potential relationship between variables. The factor contribution of each element to the principal component cannot be expressed quantitatively.

The normalized factor fraction of PCA/APCS is obtained from the results of principal component analysis, and the calculation formula is as follows (Aelion and Davis et al., 2008; Aelion and Davis et al., 2008; Davis and Aelion et al., 2009):

$$Z_{ij} = \frac{C_{ij} - \bar{C}_i}{\sigma_i}$$

Where, Z_{ij} is the concentration value after standardization (dimensionless); C_{ij} is the measured value of heavy metal concentration. $\bar{C}_i$ and σ_i are the mean concentration and standard deviation of element i, respectively.

The APCS of each heavy metal element can be obtained by subtracting the factor fraction of the 0 concentration sample from the factor fraction of each sample:

$$(Z_o)_i = \frac{0 - \bar{C}_i}{\sigma_i} = -\frac{\bar{C}_i}{\sigma_i}$$

where, $(Z_o)_i$ is the factor fraction of concentration sample 0; b_{oi} is the constant term obtained by multiple linear regression of metal element i; b_{pi} is the regression coefficient of source p to heavy metal element i.

The corresponding regression coefficients can be obtained by multiple linear regression of APCS with metal concentration data. The regression coefficient converts APCS into the contribution of the concentration of each sample to each source of pollution. The specific calculation formula is as follows:

$$APCS = Z_{ij} - (Z_o)_i$$

$$C_i = b_{oi} + \sum_{p=1}^n (APCS_p \times b_{pi})$$

$APCS_p$ is the fraction of the adjusted factor p; $APCS_p \times b_{pi}$ denotes the contribution of source p to the mass concentration of C_i ; The mean of all samples represents the mean absolute contribution of the source.

2.4 CATREG model

In order to identify the relative importance of heavy metal influencing factor variables, the CATREG model, as a non-parametric multivariate regression analysis model, can use an optimal scaling program to scale dependent and independent variables and perform the analysis of categorical and numerical variables. It is usually used to test the effects of multiple predictors on dependent variables (Almeida and Garrod, 2018; Feng and Zhao et al., 2021). Classified regression (CATREG) was selected for analysis in this study. Discrete variables and prevariables were selected into the regression. Category quantization refers to quantizing class variables by a specific nonlinear transformation and then iterating directly to find the optimal equation. CATREG model is a classical linear regression model applied with transformation variables (Yang and Wang et al., 2020).

CATREG is an econometric method used to deal with data sets containing nominal, ordinal, and interval variables. In a simple linear regression model, a response variable is predicted from m predictive variables in x to try to find a linear combination Xb that is most correlated with it. The "optimal scaling" involved makes the feasible nonlinear function analysis between Z and $\sum_{j=1}^m (b_j \varphi_j(X_i))$, and its expression is:

$$\|X^*b - Z^*\|^2 \text{ where } \|X^*b - Z^*\| = \sqrt{(X^*b - Z^*)^T (X^*b - Z^*)}$$

The classification variable h_j defines the binary indicator matrix G_j of n rows and columns l_j , where h_{ij} defines $g_{ir(j)}$ as follows:

$$\begin{cases} g_{ir(j)} = 1, h_{ij} = r \\ g_{ir(j)} = 0, h_{ij} \neq r \end{cases}$$

The $r = 1, 2, \dots, l_j$ is the running index, indicating the class number in j. If the class quantization can be expressed by y_j , then the variable of transformation can be written as $G_j y_j$. For example, the weighted sum of the predictor variables can be expressed as:

$$\sum_{j=1}^m b_j G_j y_j = X^*b$$

This is the same as the standard linear model. Finally, CATREG is equivalent to a linear regression model, which can be expressed as follows:

$$Z^* = X^*b + \varepsilon$$

In the formula, X^* represents the coefficient matrix, Z^* is the observed value vector, b is the normalized coefficient vector, and ε is the error vector. The qualitative variables are transformed into quantitative variables through the optimal scaling process. Classification variables are quantified to reflect the characteristics of the original category, and the use of nonlinear transformations allows the analysis of variables at various levels to find the best fit model.

2.5 Data source and processing

The soil heavy metals data in the study area are the survey data of our research group in 2006. A total of 342 sampling points were set from all parts of Chongqing (Fig 1). The contents of As, Cd, Cr, Cu, Hg, Mn, Mo, Ni, Pb, Sb and Zn were determined. For vegetation data, the 2008 images from Landsat8 image data were downloaded from the geo-spatial data

cloud (<http://www.gscloud.cn>), and the images with less cloud cover and an accuracy of 30m were selected. The categories of air quality, population density and water quality were derived from Statistical Yearbook (2000-2010). In order to more accurately describe the impact of industrial activities on heavy metals, gross industrial product was used to represent the intensity of industrial activities. Population distribution (2000a) is the result of China's fifth population census. Land use data (0000) ", the elevation data (DEM) (25, 0000), the slope (30 m), traffic data (25, 0000) are from resources and environment data cloud platform (<http://www.resdc.cn/default.aspx>). Soil types (1:1000000) from Chinese soil database (<http://vdb3.soil.csdb.cn/>), soil parent material (1:50 0000) from China geological map.

In this study, ArcGIS10.5 software was used to process and collect data, and spatial interpolation method was used to obtain environmental factors, such as normalized vegetation index, air comprehensive quality index, slope, soil type, soil parent material, population density, water quality category, traffic activity and gross industrial product. Then, the environmental factor values were assigned to the sampling points, and the principal component receptor model was analyzed by R language, and the CATREG model was analyzed by SPSS24.0. Finally, ArcGIS is used to complete hot spot analysis and mapping.

3. Results

3.1 Heavy metal content

The characteristics of soil heavy metals in the central urban area of Chongqing were analyzed as follows (Table 1). In the study area, the variation coefficient of As was the highest (55.71%), followed by Mo (54.69%), and the variation coefficient of Cr was the lowest (14.86%), with the maximum value of 126.094 mg·kg⁻¹ and the minimum value of 47.408 mg·kg⁻¹. Except for As and Mo elements, the coefficient of variation is greater than 0.5, showing a weakly differentiated distribution. Other heavy metal elements are all less than 0.5, including Hg, Cd, Cu, Mn, Sb, Ni, Zn, Pb and Cr, respectively, showing a uniformly weakly differentiated distribution.

Table 1 Characteristics of heavy metal content in soil in the study area

Heavy metal	Soil heavy metal content in the study area					Background value of heavy metals in soils of Chongqing(mg·kg ⁻¹)
	Max(mg·kg ⁻¹)	Min(mg·kg ⁻¹)	Mean(mg·kg ⁻¹)	Standard deviation	CV (%)	
As	21.180	1.965	5.802	3.232	55.71	6.62

Cd	0.782	0.041	0.132	0.057	43.11	0.28
Cr	126.094	47.408	76.559	11.375	14.86	74.4
Pb	42.068	12.703	25.548	4.057	15.88	28.1
Cu	76.600	6.208	23.992	8.572	35.73	24.6
Zn	144.607	37.447	75.579	13.034	17.25	81.9
Ni	62.440	15.470	30.499	6.769	22.20	31.6
Hg	0.162	0.015	0.0528	0.025	46.63	0.069
Sb	1.170	0.244	0.644	0.163	25.25	0.7
Mn	1584	107.900	573.316	184.685	32.21	615
Mo	3.197	0.100	0.560	0.306	54.69	0.5

3.2 Principal component analysis of heavy metal elements

The statistical value obtained by KMO(Kaiser-Meyer-Olkin) test is 0.870, and the concomitant probability of Bartlett spherical test is 0.000. Therefore, the data can be analyzed by principal component analysis (PCA), and the analysis results are shown in Table 2. After orthogonal Varimax rotation of the Kaiser normalized factors, two principal components with eigenvalues greater than 1 were obtained. The variance contribution rates were 48.855% and 15.788%, respectively, and the cumulative contribution rates were 64.643%. The first principal component (F1) loading heavy metal elements were Cu (0.882), Ni (0.879), Zn (0.798), Mn (0.728), As (0.718), Cr (0.688), Mo (0.661), Sb (0.632), Pb (0.629) and Hg(0.552) respectively, the lowest loading element is Cd (0.361);The second principal component (F2) with high heavy metal load was Mo (0.586), As (0.569), Hg (0.517) and Sb (0.470).

According to the receptor model of each element (Fig.2), the contributions of principal components F1 and F2 to each element were calculated respectively, and the statistical results were shown in Figure 2. The heavy metal sources of Cr, Cu, Mn, Ni, Pb and Zn were mainly controlled by F1, and the heavy metal sources of Hg were mainly controlled by F2. The contribution rates of F1 and F2 to As, Mo and Sb were not significantly different. In addition, Cd is mainly controlled by other sources. Except As and Mo, other elements are controlled by other sources to varying degrees.

Table 2 Principal component analysis/absolute principal component fraction (PCA/APCS) receptor model

Elemental	Receptor model	Sig	R ²
As	$C(As) = 2.324APCS_{F1} + 1.843APCS_{F2} + 5.802$	0.000	0.916
Cd	$C(Cd) = 0.021APCS_{F1} - 0.004APCS_{F2} + 0.132$	0.000	0.367
Cr	$C(As) = 7.834APCS_{F1} - 3.351APCS_{F2} + 76.559$	0.000	0.748
Cu	$C(Cu) = 7.575APCS_{F1} - 1.478APCS_{F2} + 23.992$	0.000	0.899
Hg	$C(Hg) = 0.014APCS_{F1} + 0.013APCS_{F2} + 0.053$	0.000	0.756
Mn	$C(Mn) = 0.728APCS_{F1} - 0.4APCS_{F2} + 30.482$	0.000	0.831

Mo	$C(\text{Mo}) = 0.203\text{APCS}_{\text{F1}} + 0.180\text{APCS}_{\text{F2}} + 0.56$	0.000	0.884
Ni	$C(\text{Ni}) = 5.96\text{APCS}_{\text{F1}} - 1.603\text{APCS}_{\text{F2}} + 30.499$	0.000	0.910
Pb	$C(\text{Pb}) = 2.555\text{APCS}_{\text{F1}} - 1.327\text{APCS}_{\text{F2}} + 25.548$	0.000	0.709
Sb	$C(\text{Sb}) = 0.103\text{APCS}_{\text{F1}} + 0.077\text{APCS}_{\text{F2}} + 0.644$	0.000	0.787
Zn	$C(\text{Zn}) = 10.420\text{APCS}_{\text{F1}} - 4.850\text{APCS}_{\text{F2}} + 75.578$	0.000	0.880

Fig.2 Sources statistics of soil heavy metal elements

3.3 Analysis of the influencing factors of heavy metal distribution

R^2 values of the fitting models for the 11 heavy metals ranged from 0.449 to 0.734, and all the fitting models passed the F test ($P < 0.05$), showing statistical significance. Through collinearity diagnosis, the variance inflation factor values of all variables ranged from 1.16 to 2.263 ($VIF < 3$), and the tolerance ranged from 0.442 to 0.862. The tolerance was high enough to ensure that the multicollinearity problem could be excluded. For the same heavy metal, the regression coefficients and significance of different influencing factors are different (Table 3). Beta is used to compare the absolute effect or contribution of each coefficient. The results of the regression coefficient test by the sources of each element, sig, are all significant by coefficient test. On the basis of significance check, the relative importance measure is helpful to explain the contribution value of CATREG model to regression.

Compared with other important values, numerical values indicate the relevant importance of these factors. Factors that significantly affect the content of As in soil are water environment (0.453), soil type (0.236) and slope (0.177); Air quality (0.332) and soil type (0.183) significantly affected the content of Cd in soil; Air quality (0.371) and NDVI (0.184) had significant effects on soil Cr content; Population density (0.539) and soil parent material (0.207) significantly affected the Cu content in soil; The distribution of Hg in soil was mainly affected by traffic activity (0.312), slope (0.223) and soil type

(0.221); Slope (0.206) and soil parent material (0.201) significantly affected the Mn content in soil; Water environment (0.374) was the most significant factor affecting soil Mo content, followed by industrial activities (0.232); Soil type (0.411) and soil parent material (0.211) significantly affected the Ni content in soil; Slope (0.313) and air quality (0.239) were significant factors affecting Pb content in soil; Soil type (0.493) and population density (0.155) significantly affected the content of Sb in soil; Soil parent material (0.472) and slope (0.324) significantly affected the content of Zn in soil.

Table 3 Importance of different environmental factors on the distribution of heavy metals

Influence factor	As	Cd	Cr	Cu	Hg	Mn	Mo	Ni	Pb	Sb	Zn
Transportation activities	-0.006	0.041	-0.011	0.004	0.312	0.005	0.001	0.116	-0.001	0.01	0.216
Industrial activity	0.006	0.016	-0.018	0.072	0.001	0.08	0.232	0.06	0.098	0.04	0.025
Air quality	0.101	0.332	0.371	0	0.016	0.11	0.101	0.056	0.239	0.023	0.071
Soil parent material	-0.065	0.25	0.034	0.207	0.018	0.201	0.004	0.211	0.224	0.128	0.472
Slope gradient	0.177	0.149	0.181	0.002	0.223	0.206	0.086	0.05	0.313	0.08	0.324
Density of population	0.069	0.002	0.012	0.539	0.062	0.163	0.145	0.005	0.174	0.155	0.009
Agrotype	0.236	0.183	0.112	-0.017	0.221	0.066	0.019	0.411	-0.018	0.493	-0.004
NDVI	0.03	0.009	0.184	0.015	0.001	0.136	0.037	-0.013	0.036	0.046	-0.136
Water environment	0.453	0.017	0.134	0.178	0.147	0.034	0.374	0.106	-0.065	0.024	0.021

3.4 Analysis of spatial distribution of heavy metals in soil

According to the importance of the influence of different environmental factors on the distribution of heavy metals in Table 4, the map and analysis were made according to the maximum influence factor of each heavy metal, and the corresponding relationship between the distribution of heavy metals in soil and the spatial distribution of environmental factors was revealed through the hot spot analysis of heavy metals in soil (Fig.3).

The highest hot spot values (99% confidence interval) of soil heavy metal As in the study area were mainly distributed in the north and west of the study area. High hot spot values (95% confidence interval) and high hot spot values (90% confidence interval) are distributed in a wide range, located in the north and west of the study area, and in the east of the concentrated distribution area, adjacent to the secondary water environment area. Overall, As element has a great overlap with the secondary water environment area. The highest hot spot value of soil heavy metal Cd in the study area is mainly concentrated in the southwest of the study area, and its air quality comprehensive index is at the overall medium level (4.22-4.23); The high hot spot values were concentrated in the western region, and the AQI was between 4.24 and 4.32. The high hot spot values are mainly distributed in the northern and central regions, and the AQI range is mainly less than 4.05 and 4.24 to 4.32

Fig.3 Spatial corresponding distribution and influencing factors of soil heavy metal hot spots: As(left) and Cd(right)

The Cr hot spot values of soil heavy metals in the study area were distributed in the western part of the study area, and the air quality composite index was mainly concentrated in the area with good air quality composite index, such as the area less than 4.05 and the area from 4.06 to 4.21 (Fig.4). The hot spot values of Cu in soil are mainly distributed in the northern, western and eastern regions, and The areas with the highest hot spot values are mainly distributed in the surrounding areas with population density greater than 3000/km² and 1000 to 3000/km².

Fig.4 Spatial distribution and influencing factors of soil heavy metal hot spots: Cr(left) and Cu(right)

234 Soil heavy metal Hg hotspots were concentrated in the middle of the study area, concentrated in the road areas less
 235 than 70m and 70 to 150m away from the road (Fig.5). The hot spots of Mn in the soil were distributed in blocks in the west,
 236 north and east, with the characteristics of slope distribution and the tendency of diffusion from the center to the periphery.

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Fig.5 Spatial distribution and influencing factors of soil heavy metal hot spots: Hg(left) and Mn(right)

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The hot spots of soil heavy metals Mo were mainly distributed in the northern, eastern and southwestern areas of the study area, and the eastern and southwestern areas were located in the secondary water environment area (Fig.6). The highest hot spots of heavy metal Ni in soils were mainly distributed in the north and northwest of the study area, mainly in the areas of yellow soil, brown soil and limestone soil. The high hot spot values were distributed in the western region, and the soil types were yellow soil, limestone soil and neutral purple soil. The higher hot spot values were distributed in the eastern and southwestern regions, which were located in the neutral purple soil and yellow soil.

mainly distributed in the surrounding areas such as the Xujiache group quartz of the Upper Triassic, the Jialingjiang group of the Lower Triassic and the Lei of the Middle Triassic, the Jialingjiang group limestone of the Lower Triassic and the Feixianguan group marl of the Lower Triassic (Fig.8).

Fig.8 Spatial distribution and influencing factors of soil heavy metal hot spots: Zn

4 Discussion

PCA is widely used to identify possible sources of interrelated heavy metals, but PCA does not consider the importance of each index on the impact of soil heavy metals, resulting in the failure to identify important indicators (Zhang and Huang et al., 2020; Shao and Hu et al., 2021). The results of this study show that the principal component analysis model can only analyze that Cr, Cu, Mn, Ni and Pb are affected by F1, Hg is affected by F2, and As, Mo, Sb, Zn and Cd are affected by other factors. Soil use and laboratory analysis at a landfill site in Enugu State, Nigeria, using PCA, identified the first principal component (36%) and second principal component (28.2%) as e-waste disposal and the third principal component (10.2%) from household and other forms of cosmetics(Mama and Nnaji et al., 2021). Principal component analysis of heavy metals in agricultural soils of Kermansha province in western Iran showed that As, Cd, Cu, Pb, Se and Zn were anthropogenic, while Cr and Ni were geo-derived (Rahman and Jolly et al., 2021).Based on the analysis of heavy metals in the park soils of Delhi, India, PC1 has a high load of Fe, Mn, Co and Zn, which indicates that the crustal origin is mainly influenced by human beings; The content of Ni and Zn in PC2 is high, which is mainly from electroplating and electroplating process (Siddiqui and Khillare et al., 2020). Principal component analysis can only analyze the approximate source points of soil heavy metals, but does not specify the specific influencing factors. Therefore, on this basis, this paper uses CATREG model to further analyze the relationship between heavy metals and environmental factors.

Classified regression is a suitable method to identify the factors affecting soil heavy metal content. Previous studies have shown that Austrian scholar Claudia Gundacker(2009) conducted a bivariate analysis through classification regression (CATREG) to explain the relationship between Pb and Hg exposure and genetic background. Yang (2020) firstly applied the classification regression analysis to the analysis of soil heavy metals, and found that the soil parent material, soil type, land use type and industrial activities were the main factors affecting the content of heavy metals in the soil of Beijing. This study found that soil, topography, population density, air quality, traffic and water sources were the main sources of heavy metals in the soil of Chongqing city.

4.1 Heavy metal content analysis

Previous studies on heavy metals have shown that different land use types lead to different levels of soil heavy metal pollution (Ma and Jia et al., 2017). The results of this study show that the average levels of Mn, Cr, Zn, Ni, Pb, Cu, As, Sb, Mo, Cd and Hg in the soil of Chongqing city center were 573.32, 76.56, 75.58, 30.50, 25.55, 23.99, 5.80, 0.64, 0.56, 0.13, 0.05mg/kg, respectively. Only Cr and Mo exceeded the background value of heavy metals in Chongqing soil by 74.4 mg/kg and 1.12mg/kg. Previous studies have shown that according to the National Environmental Protection Administration of China (GB156181995), the concentrations of Pb, Cu, Cr, As, Hg, Ni and Zn in the soil in Tongnan District of Chongqing are lower than the safe threshold concentration, and the concentrations of Cd are higher than the safe threshold (Ma and Jia et al., 2017). The contents of heavy metals Cd, Hg, Cr, Cu, Zn and Pb in the soil of Rhizus monkey peach garden in Qianjiang District of Chongqing are higher than the national background value, and the contents of heavy metals in the soil of different orchards are also different (Yan and Ding et al., 2021). Compared with foreign countries, the contents of As and Cu in agricultural soils of Eggred County in southern Iran are close to the background values, while the contents of Cd are higher than the corresponding background values (Sabet Aghlidi and Cheraghi et al., 2020). Therefore, the degree of human disturbance in different areas leads to different levels and concentrations of heavy metals in the soil.

4.2 Environmental factors affecting heavy metals

4.2.1 Soil and Terrain

Soil types have significant effects on spatial hot spot distribution patterns of Ni and Sb in the study area. On the whole, the heavy metals in the two soils were distributed banded along the trend of yellow soil, yellow limestone soil and lime (rock) soil. Harley T. Davis(2009) pointed out that different soil types have different parent material, drainage capacity, texture pH and pH, which have different effects on the migration and accumulation of heavy metals, leading to the depletion and enrichment of some elements in different land types. Soil types such as yellow soil and calcareous soil where Ni and Sb are concentrated have poor drainage, and their parent materials are all kinds of acidity, basic rocks and carbonate, which are slightly acidic or alkaline. In addition, factors such as soil pH and depth of underground water table should be considered.

Soil parent material is one of the factors that affect the concentration of heavy metals(Xu and Zhang et al., 2021). Zn

elements in the surrounding areas, such as the Xujiache Longstone Sandstone of Upper Triassic, Jialingjiang Formation of Lower Triassic and Leikoupo Formation of Middle Triassic, are distributed in clusters or bands. Previous studies have shown that a potential Zn conversion pathway exists in the subsurface environment, and found that sphalerite is the main phase of zinc concentrate, while quartz, iron-rich sphalerite (ZnS) and zinc oxide (ZnO) are the main phase of roadside dust.(Kwon and Lee et al., 2017).These results indicate that the spatial distribution of Zn in this region is closely controlled by soil parent material, which is of important reference significance for the interpretation of its source and distribution.

In the study area, mountains and slopes were cut into a large number of urban clusters by rivers. Slope factor is particularly important for the analysis of the source of heavy metals.± The hot spots of Mn in the soil were distributed along the slope direction and tended to diffuse from the center to the periphery, and the slope of the hot spots of Pb was mostly between 10° and 25°. The results showed that heavy metals accumulated in slope soil to a certain extent under the influence of long-term soil erosion, slope runoff and slope gravity settlement(Deng and Chen et al., 2018)。

4.2.2 Population density and air quality

Different population density is closely related to the accumulation of heavy metal Cu in soil. Population density is one of the important sources of soil heavy metal(Manuel Trujillo-Gonzalez and Aurelio Torres-Mora et al., 2016)。 Based on the analysis of the physical and chemical properties, total and chemical forms of Cu in cities and soils with different population densities in Murcia, southeast Spain, the study shows that the behavior of Cu in soil dust and soil is affected by physical and chemical properties and total concentrations(Moros and Martinez-Sanchez et al., 2009). Heavy metals in road dust in Rafsanjan, Iran were investigated. The enrichment factor (EF) evaluation results showed that Cu was the most concerned pollutant. It was found that Cu was mainly derived from human factors, such as industrial and chemical activities, and heavy traffic(Mirzaei Aminiyan and Baalousha et al., 2018). H. Khademi(2020) proposed that the concentration of Cu was significantly correlated with particle size, and found that the particle size dependence of metal concentration and element enrichment degree in street dust were higher than those in urban soil, indicating that anthropogenic pollution contributed more to dust. This study shows that the higher the population density in Chongqing downtown, the greater the content of heavy metal Cu in the soil.

The results of this study show that the heavy metals Cr and Cd in the soil of Chongqing city center mainly come from the air environment, and the hot spot value of Cr is distributed in the areas with high air quality comprehensive index, on the contrary, the hot spot value of Cd is mainly distributed in the areas with medium air quality comprehensive index. Previous studies have shown that in the mountainous region of Asturias in the northwest of Spain, the sources of Cr and Cd in the soil are mainly from local air pollution-related factors, such as heavy metals released by vegetation combustion (Fernández and Cotos-Yáñez et al., 2018). Xiaojia Chen(2019) collected road dust samples from Beihai and Shanghai in order to explore the differences of heavy metal characteristics in air quality of different environments, and found that Cd is a traffics-derived

metal, and Cr may be affected by natural sources. Air pollutants containing Cr and Cd were produced after the burning of peat in Malaysia, and the two heavy metal elements were found to be moderately enriched in the soil by atmospheric deposition (Othman and Latif, 2013). In conclusion, the characteristics of soil Cr and Cd heavy metals are different due to the different environmental air quality levels in different regions.

4.3 Transport and Water

Urban street dust is a mixture of mineral composition, organic matter and elemental carbon. Heavy metals contained in the dust of motor vehicles and building smoke on traffic roads are one of the main sources of urban dust (Amato and Pandolfi et al., 2009; Kim and Park et al., 2016). The heavy metal Hg in the soil of the study area was concentrated in the areas with dense roads and close to roads, indicating that the high content of Hg was one of the main substrates of street dust in the study area. Previous studies have shown that the highest average concentrations of mercury in TSP and dry deposition occur in industrial areas, but in industrial areas, metal product manufacturing and heavy traffic are the sources of high concentrations of mercury at industrial sampling sites (Fang and Lo et al., 2011). In addition, Akhter, M.S.(1993) studied the dust of 106 streets and families in Bahrain and concluded that motor vehicles were the main source of heavy metals in the dust samples, revealing the close relationship between heavy metals in Bahrain and population density and traffic. The above studies are consistent with the relationship between Hg element and traffic road in the study area, which indicates that both industrial activities and traffic are important sources of Hg. However, the influence of industrial production on Hg in the study area remains to be discussed.

Water is an important carrier and pathway for the movement of heavy metals. The Yangtze River and the Jialing River traversing the study area are the core factors for human survival and industrial development. Surface runoff and the industrial and agricultural production of soil in drinking water sources can import a large amount of heavy metals into the environment, resulting in the accumulation of heavy metals in the soil in drinking water sources (Davis and Aelion et al., 2009; Liu and Jiang et al., 2018). The hot spot distribution of As and Mo in soil was similar, and mainly distributed in the secondary water environment area in the east of the study area in three aggregates. Ezekwe(2012) explored the relationship between heavy metal pollution and groundwater in the Stone Horn mining area in southeastern Nigeria, and concluded that there was a close relationship between heavy metal pollution and water quality. Some heavy metals in river sediments in the water source area mainly come from the leaching of the surrounding soil. In this study, the eastern area where As and Mo are enriched is the downstream area of the river in the study area, which is presumed to be the joint result of heavy metals moving along the river and enrichment in the surrounding area.

5 Conclusion

The main sources of heavy metals in soil were analyzed, and the heavy metal data were analyzed by using principal component analysis method and classification regression method. Principal component receptor model is widely used to

determine the source of heavy metals, but the results are not accurate enough. Since the CATREG model cannot obtain all the data of the influencing factors, the results may have some deviation, but this method can accurately identify the specific category of the influencing factors. In general, in addition to normalized vegetation index and gross industrial product, slope, soil type, soil parent material and population density are the important factors that affect the soil heavy metal content in Chongqing. The results show that As and Mo hotspots are mainly concentrated in the area with secondary water environment, Cd and Cr hotspots are concentrated in the area with air quality index 4.06-4.23, Mn and Zn hot spots are concentrated in the area with Triassic parent material, Ni and Sb hot spots are concentrated in the area with yellow soil and limestone (rock) soil, and Pb hot spots are concentrated in the area with slope of 10°~25°.Hg hot spots are concentrated in the area with road distance less than 150m, and Cu hot spots are concentrated in the area with population density >1000/km². On the whole, the heavy metal pollution areas are mainly concentrated in the north, east and middle of the central city. The research results provide reference for soil pollution prevention and control.

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