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RESEARCH ARTICLE

Identifying factors that influence soil heavy metals by using categorical regression analysis: A case study in Beijing, China

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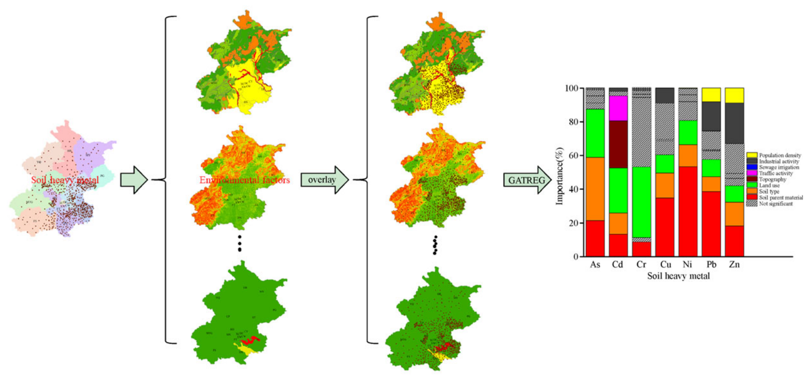
HIGHLIGHTS

- A method was proposed to identify the main influence factors of soil heavy metals.
- The influence degree of different environmental factors was ranked.
- Parent material, soil type, land use and industrial activity were main factors.
- Interactions between some factors obviously affected soil heavy metal distribution.

GRAPHIC ABSTRACT



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ABSTRACT

Identifying the factors that influence the heavy metal contents of soil could reveal the sources of soil heavy metal pollution. In this study, a categorical regression was used to identify the factors that influence soil heavy metals. First, environmental factors were associated with soil heavy metal data, and then, the degree of influence of different factors on the soil heavy metal contents in Beijing was analyzed using a categorical regression. The results showed that the soil parent material, soil type, land use type, and industrial activity were the main influencing factors, which suggested that these four factors were important sources of soil heavy metals in Beijing. In addition, population density had a certain influence on the soil Pb and Zn contents. The distribution of soil As, Cd, Pb, and Zn was markedly influenced by interactions, such as traffic activity and land use type, industrial activity and population density. The spatial distribution of soil heavy metal hotspots corresponded well with the influencing factors, such as industrial activity, population density, and soil parent material. In this study, the main factors affecting soil heavy metals were identified, and the degree of their influence was ranked. A categorical regression represents a suitable method for identifying the factors that influence soil heavy metal contents and could be used to study the genetic process of regional soil heavy metal pollution.

1 Introduction

Soil heavy metals can be absorbed by the roots of plant roots, such as rice and vegetables, and enter the food chain, thereby threatening human health (Khan et al., 2008;

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Williams et al., 2009; Zhuang et al., 2009; Niu et al., 2013; Cai et al., 2015). Identifying the main factors that influence soil heavy metals may provide a basis for analyzing the causes of soil heavy metal pollution (Ettler et al., 2006; Komárek et al., 2008; Sucharova et al., 2011; Sun et al., 2012). High contents of soil heavy metals are a result of multiple factors, and the factors that affect their contents in soil are mainly natural and anthropogenic. The natural factors include the soil parent material (Salonen and Korkka-Niemi, 2007; Nael et al., 2009), soil types (Chen et al., 2002), and topography (Wang et al., 2008). The anthropogenic factors mainly include industrial activity (Li et al., 2014; Yang et al., 2018), sewage irrigation (Khan et al., 2008), agricultural inputs (Wu et al., 2013), atmospheric deposition (Bi et al., 2009), land use types (Kuusisto-Hjort and Hjort, 2013), E-waste dismantling (Zhao et al., 2019), and traffic activity (Guan et al., 2018).

The methods for identifying factors that influence soil heavy metals mainly include statistics and geostatistical analyses, the isotope tracer technique, and the geographical detector method. Statistical analysis methods include the correlation analysis, principal component analysis, and cluster analysis. By determining the correlation among elements, elements with good correlation are extracted into the same classification (Facchinelli et al., 2001). Influencing factors for different classifications are deduced through prior knowledge or investigation (Borůvka et al., 2005; Francouría et al., 2009; Acosta et al., 2010; Qu et al., 2013). A hotspot analysis is used in geostatistics to identify contaminated areas (Zhang and McGrath, 2004; Zhang et al., 2008). By using a spatial overlay analysis of the contaminated area and other influencing factors (natural and anthropogenic factors), the factors that influence soil heavy metals are analyzed based on their degree of spatial overlap (Facchinelli et al., 2001; Wang and Lu, 2011; Lu et al., 2012). Isotopic tracer technology uses the isotopic ratios of different sources to determine objectively the main source of soil pollutants (Gao et al., 2013; Rua-Ibarz et al., 2016; Ishii et al., 2017; Xu et al., 2017). The geographical detector is based on the spatial variability of geographic variables, it can assess the impact of environmental variables on the dependent variable. By sorting out the degree of variation of environmental variables, the main factors that affect the dependent variable can be identified (Wang et al., 2010; Wang et al., 2016).

Soil heavy metals are affected by both numerical variables and categorical variables. At the same time, nominal, ordinal, and numerical variables could be scaled by categorical regression (CATREG) simultaneously. For example, Gundacker et al. (2017) used CATREG to calculate the contribution of predictor variables to variability of the response variables and found that the area of residence and maternal age could be confirmed as significant and independent determinants of cord blood lead, while area of residence was the only significant predictor of maternal blood lead. Ikeda et al. (2017) used CATREG to examine the effects of sleep disturbances on depression and found that IS (global insomnia score) was significantly correlated with depression score. Çilan and Can (2014) used CATREG to determine the factors affecting MBA students' success and found that age and marital status significantly affected their success. Based on these reasons, CATREG was advocated as a promising tool to identify factors that influence soil heavy metals. After the environmental factors were assigned to soil heavy metal data, the degree of influence of different factors on soil heavy metal contents was analyzed via the CATREG, which represents the first application of the CATREG method for soil heavy metals. We think this method is especially suitable for analyzing the variables that are both numerical and categorical. We tried to see its validity for identifying influencing factors of soil heavy metals. Although this method is rarely applied at present, it can provide a reference for source tracing of soil heavy metal pollution.

2 Materials and methods

2.1 Study area

Beijing is the capital of China and located on the northern North China Plain, with its center located at 39.9°N and 116.4°E. Beijing has 18 administrative counties with a total area of 16,411 km^2 and a population of 20.69 million in 2012. The terrain gradually decreases from north-west to south-east, and an orderly arrangement of mountains, hills, and alluvial plains occurs from the north-west to the south-east with more than 2000 m of height difference. The main river systems include Juma, Yongding, Beiyun, Chaobai, and Jiyun. Among these rivers systems, Liangshui and Xinfeng are major rivers that receive waste discharge. In 2001, Beijing had 13,891 km of road mileage, 335 km of highway mileage, and 4,312 km of urban road mileage (Fig. 1).

2.2 CATREG

As for the factors that influence soil heavy metals, some variables from survey data are often categorical. In this case, traditional linear regression could not be suitable for data analysis. CATREG is a non-parametric multiple regression analysis could be implemented when variables are all categorical or both categorical and numeric. So CATREG could represent a preferred alternative modeling method.

In the simple linear regression model, in order to predict a response variable **z** from m predictor variables in **X**, we try to find a linear combination **Xb** that correlates maximally with **z.** In the Gifi system, "optimal Scaling" maximizes the correlation between (**Z**) and $\sum_{j=1}^{m}\left(b_j\varphi_j(X_j)\right)$

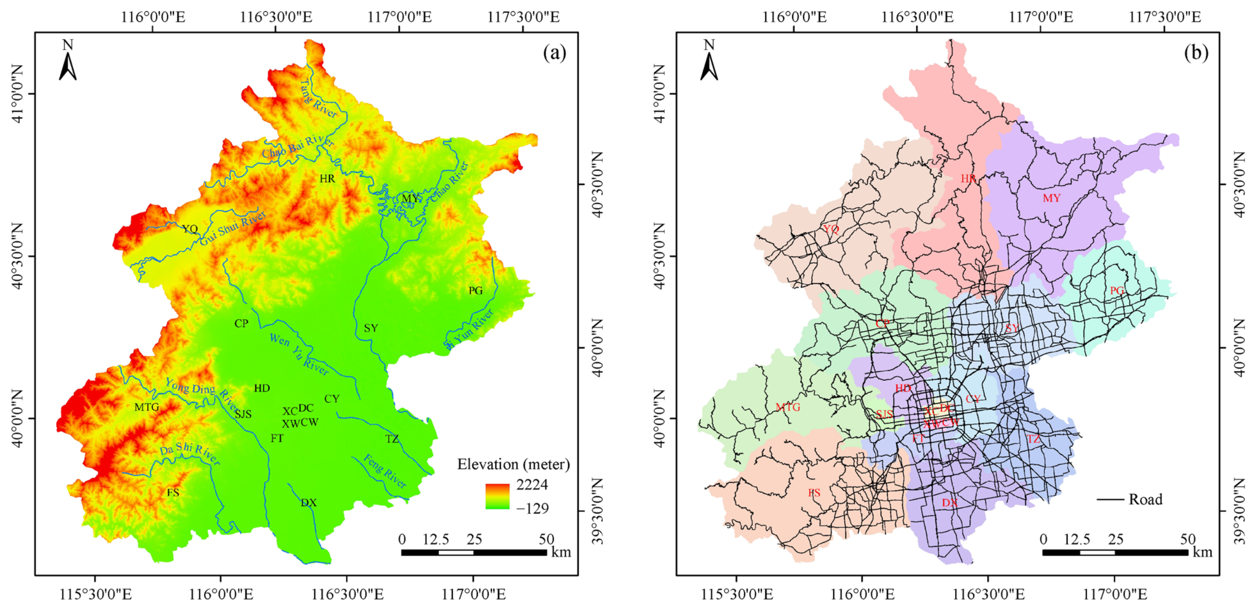


Fig. 1 The basic information of the study area. (a) Spatial distribution of river systems and terrain; (b) Spatial distribution of traffic.

over feasible nonlinear functions.

$$\|X^{*}b-Z^{*}\|^{2} \quad \text{where} \quad \|X^{*}b-Z^{*}\| = \sqrt{\left((X^{*}b-Z^{*})^{T}(X^{*}b-Z^{*})\right)}. \tag{1}$$

A categorical variable $\mathbf{h}_{\mathrm{j}}$ defines a binary indicator matrix $\mathbf{G}_{\mathrm{j}}$ with n rows and l_{j} columns, where l_{j} denotes the number of categories. Elements $\mathbf{h}_{\mathrm{ij}}$ then define elements $g_{\mathrm{ir(j)}}$ as follows:

$$\begin{cases} g_{ir(j)}=1, & h_{ij}=r, \\ g_{ir(j)}=0, & h_{ij}\neq r, \end{cases} \tag{2}$$

where $r=1,2,\ldots,l_{\mathrm{j}}$ is the running index indicating a category number in variable j. If category quantifications are denoted by $\mathbf{y}_{\mathrm{j}}$, then a transformed variable can be written as $\mathbf{G}_{\mathrm{j}}\mathbf{y}_{\mathrm{j}}$ and, for instance, a weighted sum of predictor variables as $\sum_{j=1}^{m} b_j G_j y_j = X^{*}b$, which is the same as the standard linear model (Meulman, 1997). Finally, a CATREG model is equivalent to a linear regression model and can be expressed as given below:

$$Z^{*}=X^{*}b+\varepsilon. \tag{3}$$

In Eq. (3), $\mathbf{X^{*}}$ represents the coefficient matrix, $\mathbf{Z^{*}}$ is the vector of observations, $\mathbf{b}$ is a vector of standardized coefficients, and $\boldsymbol{\varepsilon}$ is the vector of errors (Shrestha, 2009).

Qualitative variables were turned into quantitative ones by the optimal scaling process. Nominal, ordinal, and numerical variables could be scaled by CATREG simultaneously. Categorical variables are quantified to reflect the characteristics of original categories (Çilan and Can, 2014). Using nonlinear transformations allows variables to be analyzed at a variety of levels to find the best-fitting model (Meulman et al., 2005; Mccormick and Salcedo, 2017). CATREG has been widely applied in the fields of medicine and sociology (Gundacker et al., 2010; Çilan and Can, 2014; Gundacker et al., 2017; Ikeda et al., 2017).

2.3 Environmental factors

Soil heavy metals are affected by natural and anthropogenic factors. As shown in Table 1 and Fig. 2, eight common influencing factors were selected in this study. The natural factors included soil parent material, soil types, and topography. The anthropogenic factors included land use types, traffic activity, sewage irrigation, industrial activity, and population density.

1) Soil parent material is the main source of soil heavy metals. The soil heavy metal contents differ in each soil parent material (Wang et al., 2005). According to the characteristics of soil development, there are five kinds of soil parent materials (Ordovician, alluvial-diluvial, alluvial, Changcheng-Jixian of the Proterozoic, and Archean) in Beijing (Qiao et al., 2018). For Ordovician and Changcheng-Jixian of the Proterozoic, dolomite is the dominant lithology. Gneiss and amphibolite are the dominant lithologies of Archean.

2) Soil properties such as the clay mineral, oxide, and organic matter contents, differ for each soil type. The adsorption degree of heavy metals on soils is also different, which affects the migration behavior of heavy metals in the surface environment (Dube et al., 2001). According to the soil genetic classification standard (Shi et al., 2004), there are mainly four soil types (alluvial soil, skeleton soil, cinnamon soil, and demeasdow soil) in Beijing.

Table 1 Selected independent variables

Independent variables	Type	Categories
Soil parent material	Nominal	1 = Ordovician, 2 = alluvial-diluvial, 3 = alluvial, 4 = Changcheng-Jixian of Proterozoic, 5 = Archean
Soil type	Nominal	1 = alluvial soil, 2 = skeleton soil, 3 = cinnamon soil, 4 = demeasdow soil
Land use type	Nominal	1 = clean area, 2 = vegetable plot, 3 = grassland, 4 = paddy field, 5 = orchard, 6 = wheat land
Slope (°)	Numeric	–
Traffic activity (m)	Numeric	–
Sewage irrigation	Ordinal	1 = Liangshui river sewage irrigation area, 2 = Xinfeng river sewage irrigation area, 3 = no sewage irrigation
Industrial production (million yuan/km^2)	Numeric	–
Population density (people/km^2)	Numeric	–

3) A greater slope will generate more runoff, which will erode more soil particles (Kraus and Wiegand, 2006). Soil particles carry heavy metals downstream, which changes the original spatial distribution pattern of soil heavy metal contents (Ciszewski et al., 2012). The slope data of each sampling point were obtained through a spatial analysis using ArcGIS software.

4) Different land use types determine the intensity of agricultural inputs, such as pesticides and fertilizers, which have different effects on the soil heavy metal contents (Yang et al., 2009; Xia et al., 2011; Kuusisto-Hjort and Hjort, 2013). The study area has five land use types (vegetable plot, grassland, paddy field, orchard, and wheat land) and clean area. The clean area mainly refers to natural soil that is far away from the city and has little human disturbance (Chen et al., 2004).

5) Traffic activity may result in soil heavy metal pollution on both sides of the road. The pollutants were mainly distributed within 50 m of both sides of the road, and the soil heavy metal contents were approximately equal to the soil background value 70-150 m away from the road (Leonzio and Pisani, 1987; Swaileh et al., 2004). The distance function of ArcGIS was used in this study to calculate the distance between soil samples and roads.

6) Sewage irrigation may result in soil heavy metal pollution, especially for both sides of sewage-irrigated rivers. Liangshui and Xinfeng were the two main rivers receiving waste discharge in Beijing (Yang et al., 2008). Given the different degrees of sewage irrigation and the irrigation characteristics of farmland soil in Beijing, Beijing was divided into three regions: the Liangshui river sewage irrigation area, the Xinfeng river sewage irrigation area, and the non-sewage irrigation area.

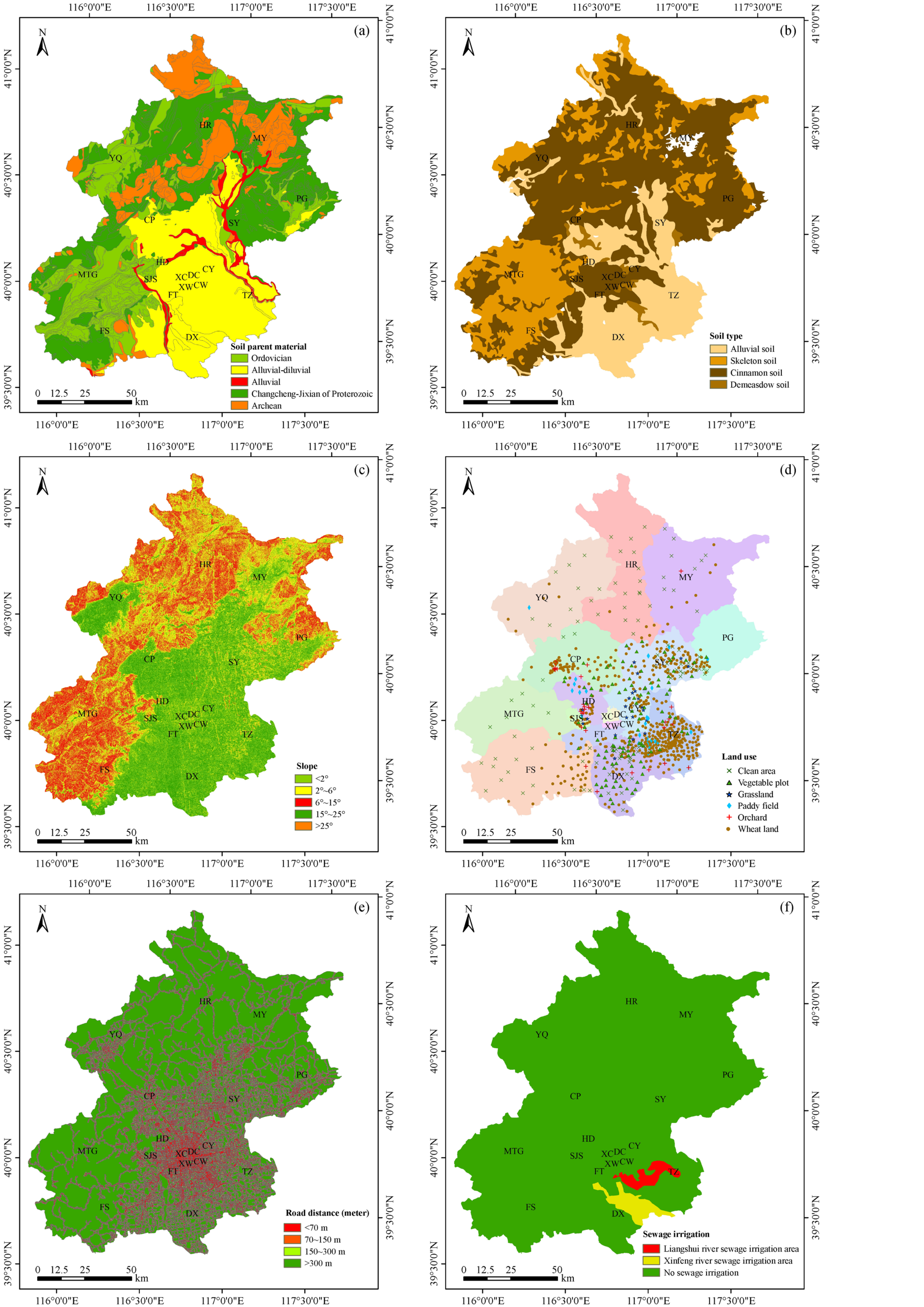
7) Waste gas, waste water, and solid waste generated by industrial activity are important factors that lead to soil heavy metal pollution (Kabir et al., 2012). Industrial production was adopted in this study to characterize industrial activity (Qiu et al., 2016; Qiao et al., 2018). Ultimately, an intersect analysis was used to obtain the industrial production of each soil sample using ArcGIS software.

8) Population density has a significant effect on heavy metal contents in most environmental media (Nriagu and Pacyna, 1988). The denser the population, the more frequent the human activity and the higher the disturbance to the natural environment. The population of sampling points in different districts was obtained by an intersect analysis.

2.4 Data source and processing

The soil heavy metal data for the study area were survey data obtained by our group in 2000 (Yang et al., 2008; Zheng et al., 2008). A total of 844 soil samples were collected from all over Beijing City (Fig. 3). The contents of As, Cd, Cr, Cu, Ni, Pb and Zn were determined. The industrial output value of each administrative region in Beijing was obtained from the statistical yearbook (1995–2000). To describe the effect of industrial activities on heavy metals more accurately, the industrial output value per square kilometre was used to characterize the strength of industrial activity (Qiu et al., 2016). The population distribution (2000a) is the result of China's fifth population census. Land use data (1:100000), altitude data (DEM) (1:250000), and traffic data (1:250000) were obtained from the Resource and Environmental Data Cloud Platform (http://www.resdc.cn/Default.aspx). Soil types (1:1000000) were obtained from the China Soil Database (http://vdb3.soil.csdb.cn/), and the soil parent material (1:500000) was obtained from the Geological Map of China (Ma, 2002).

The influencing factors were identified via CATREG using SPSS 24.0 software. A multi-factor variance analysis was adopted to conduct a factor interaction analysis using SPSS 24.0. A hotspot analysis (Moran's I), spatial distribution, and mapping of the data were completed using ArcGIS 10.2 software.


(a)
Soil parent material
Ordovician
Alluvial-diluvial
Alluvial
Changcheng-Jixian of Proterozoic
Archean
(b)
Soil type
Alluvial soil
Skeleton soil
Cinnamon soil
Demeasdow soil
(c)
Slope
<2°
2°~6°
6°~15°
15°~25°
>25°
(d)
Land use
Clean area
Vegetable plot
Grassland
Paddy field
Orchard
Wheat land
(e)
Road distance (meter)
<70 m
70~150 m
150~300 m
>300 m
(f)
Sewage irrigation
Liangshui river sewage irrigation area
Xinfeng river sewage irrigation area
No sewage irrigation
HR
MY
YQ
PG
CP
SY
HD
MTG
SJS
XC
DC
CY
XW
CW
FT
TZ
FS
DX
0 12.5 25 50 km
116°0'0"E
116°30'0"E
117°0'0"E
117°30'0"E
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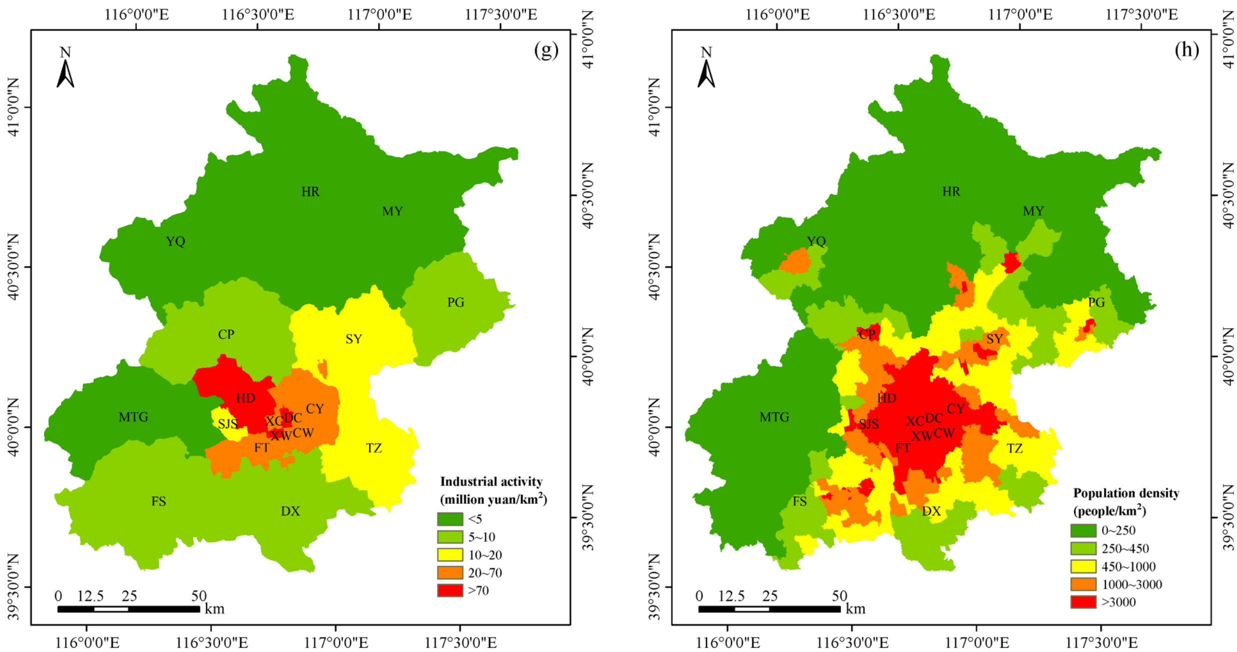

Fig. 2 Influence factors of soil heavy metals. (a) Soil parent material; (b) Soil types; (c) Slope; (d) Land use types; (e) Road distance; (f) Sewage irrigation; (g) Industrial activity; (h) Population density.

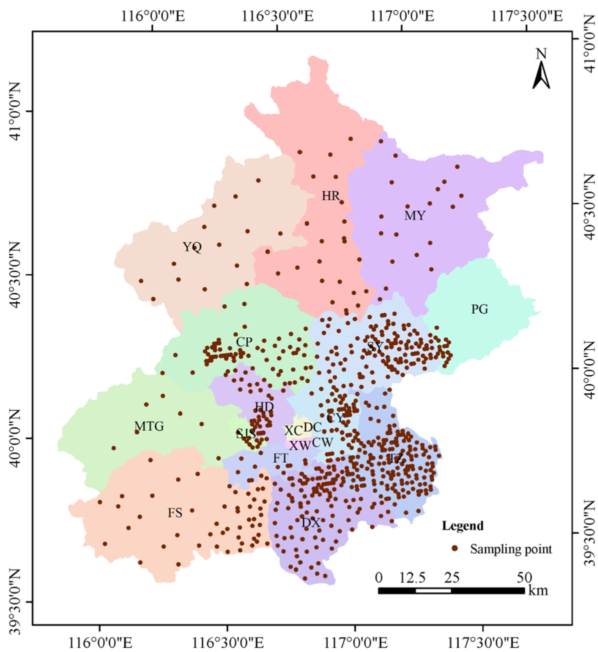

Fig. 3 Spatial distribution of samples.

3 Results

3.1 Identification of the main factors affecting the spatial distribution of soil heavy metals

For the seven heavy metals, the R^2 values of fitting models were between 0.054 and 0.169, and all the fitting models passed the F test ($p < 0.05$) and were statistically significant. The tolerance of all variables was high enough to assure the exclusion of the multicollinearity problem.

For the same heavy metal, the regression coefficients and significance of different influencing factors were different (Table 2). The soil parent material, soil type, and land use type had a significant influence on the soil As, Cd, Cr, Cu, Ni, Pb, and Zn. Industrial activity had a significant influence on the soil Cd, Cu, Pb, and Zn. Population density had a significant influence on the soil Pb, and Zn. Topography and traffic activity had significant effects on the soil Cd.

On the basis of the significance test, Pratt's measure of relative importance aided in interpreting the predictor contributions to the regression (Table 3). Large individual importance values relative to other importance values corresponded to predictors that are crucial to the regression (Pratt, 1987). The numerical values refer the relative importance of these factors. For example, the factors that significantly affected the soil As content were the soil type, land use type, and soil parent material. Similarly, we could clearly obtain the factors that significantly affected the other heavy metals in Table 3. In general, the soil parent material, soil type, land use type, and industrial activity were the main factors that affected soil heavy metals in Beijing. Moreover, population density also had a certain effect on the soil Pb and Zn.

3.2 Influence of factor interactions on soil heavy metal contents

As shown in Table 4, the distribution of soil As, Cd, Pb,

Table 2 CATREG coefficients and significance test of different factors

Influence factor	As		Cd		Cr		Cu		Ni		Pb		Zn	
	Beta	Sig	Beta	Sig	Beta	Sig	Beta	Sig	Beta	Sig	Beta	Sig	Beta	Sig
Soil parent material	0.124	0	0.147	0	0.133	0	0.258	0	0.278	0	0.244	0	0.156	0
Soil type	0.178	0	0.111	0	0.078	0.001	0.183	0	0.094	0.007	0.126	0	0.158	0
Land use type	0.124	0	0.189	0	0.22	0	0.121	0	0.129	0	0.1	0	0.097	0
Topography	−0.161	0	0.185	0	−0.242	0	0.164	0.206	−0.17	0.128	0.067	0.272	0.056	0.45
Traffic activity	−0.046	0.295	0.161	0	0.045	0.496	0.05	0.388	−0.062	0.162	−0.017	0.855	0.077	0.185
Sewage irrigation	−0.045	0.251	−0.073	0.067	−0.038	0.214	−0.177	0	−0.041	0.228	−0.139	0	−0.173	0
Industrial activity	0.013	0.732	0.077	0.013	0.032	0.374	0.115	0.001	0.018	0.599	0.147	0	0.168	0
Population density	0.015	0.685	−0.006	0.845	0.022	0.482	0.004	0.912	0.01	0.743	0.098	0.003	0.092	0.008

Table 3 Importance of different factors

Influence factor	As	Cd	Cr	Cu	Ni	Pb	Zn
Soil parent material	0.214	0.133	0.087	0.347	0.532	0.386	0.182
Soil type	0.373	0.126	0.026	0.147	0.130	0.087	0.141
Land use type	0.288	0.266	0.418	0.108	0.144	0.104	0.097
Topography	0.033	0.280	0.414	0.083	0.112	0.051	0.042
Traffic activity	0.046	0.154	0.018	0.007	0.040	0.007	0.032
Sewage irrigation	0.033	0.018	0.022	0.213	0.036	0.110	0.177
Industrial activity	0.006	0.024	0.011	0.092	0.002	0.174	0.241
Population density	0.007	0.000	0.004	0.001	0.003	0.082	0.089

and Zn were obviously influenced by a series of interactions. For example, the interaction between industrial activity and other factors (population density, sewage irrigation and traffic activity) significantly affected the Cd, Pb and Zn contents. The interaction between land use type and the other two factors (sewage irrigation and traffic activity) had an obvious influence on the soil As, Cd, Pb and Zn contents. In addition, the interaction between land use type and sewage irrigation and between soil parent material and soil type significantly affected the soil As and Cd contents, respectively.

Table 4 Interaction of different factors

Heavy metal	Interaction	Sig.
As	Land use type–sewage irrigation	0.003
	Population density–sewage irrigation	0.030
Cd	Soil parent material–soil type	0.021
	Land use type–traffic activity	0.026
	Industrial activity–population density	0.003
Pb	Land use type–traffic activity	0.002
	Industrial activity–sewage irrigation	0.047
Zn	Land use type–traffic activity	0.001
	Industrial activity–traffic activity	0.042

3.3 Hotspot distribution of soil heavy metals

A hotspot analysis of soil heavy metals showed that the distribution of soil heavy metals and influencing factors had a good spatial correspondence, especially factors such as industrial activity, population density, and soil parent material. As shown in Fig. 4, hotspots of some heavy metals were consistent with the population density and industrial activity. For example, the hotspots of Cu, Pb, and Zn were mostly distributed in areas with higher industrial output values and presented good correspondence with the spatial distribution of industrial activity (taking Zn element as an example in Fig. 4). In addition, the hotspots of Pb and Zn were mostly distributed in regions with higher population density (taking Zn element as an example in Fig. 4). A higher population density often means that there is more human activity, which can easily lead to the accumulation of soil heavy metals. However, soil heavy metals have complex sources and are not affected by a single factor. Therefore, the distribution of heavy metals and influencing factors would not be entirely consistent with each other. For example, Cu was affected by industrial activity and land use type. In the hotspot analysis, an area with high Cu content was consistent with the spatial distribution of industrial output values>20 million yuan/km^2. However, in the Changping District, the relatively

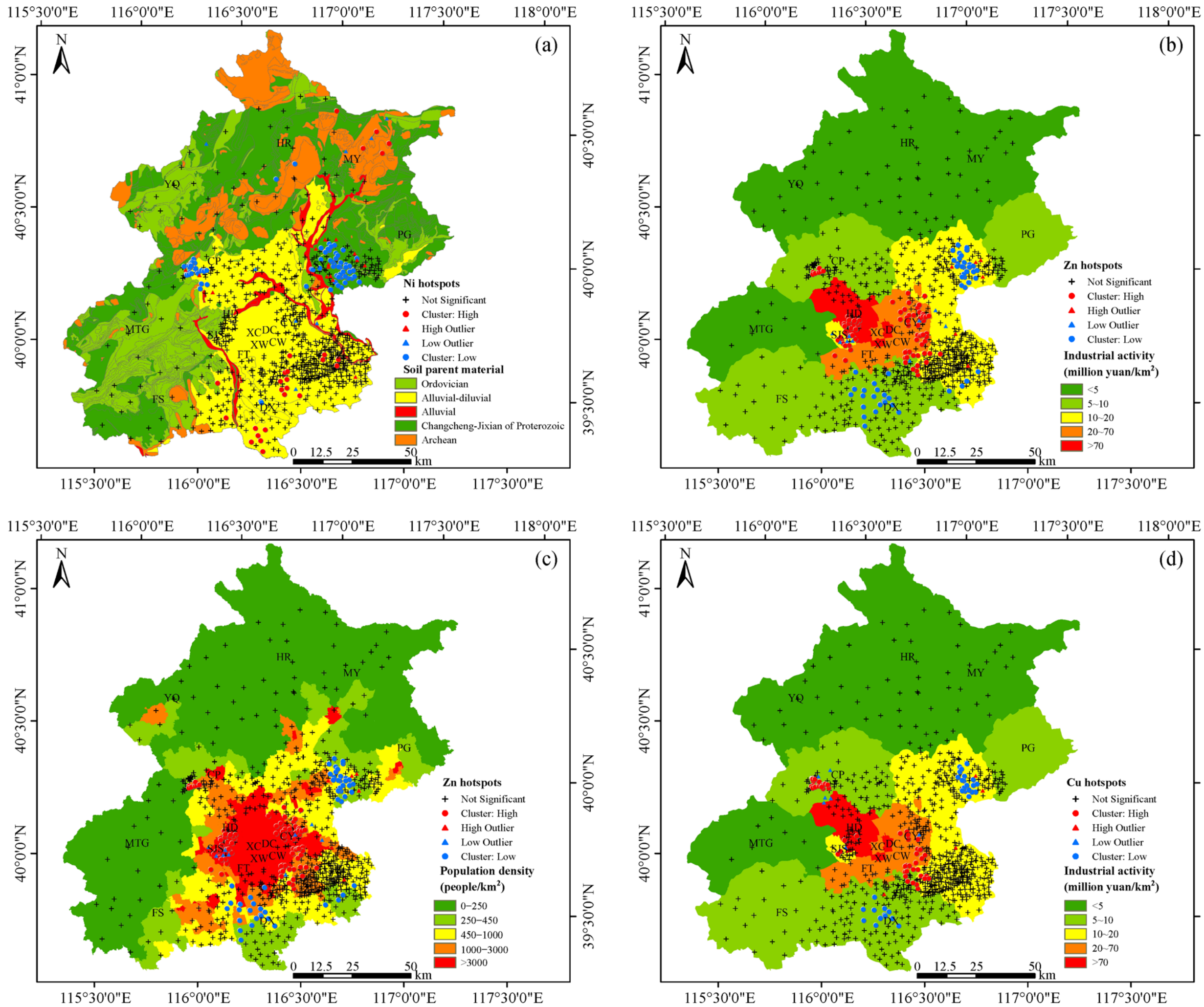

Fig. 4 Spatial corresponding distribution of soil heavy metal hotspots and influence factors. (a) The Ni hotspots and soil parent material; (b) The Zn hotspots and industrial activity; (c) The Zn hotspots and population density; (d) The Cu hotspots and industrial activity.

lower industrial output value corresponds to the Cu hotspot area. Many orchards are located in this area; thus hotspots of Cu in this area may result from the extensive use of agrochemicals at high rates. Many formulations of Cu-containing fungicides and herbicides, such as Bordeaux mixture, copper oxychloride and $CuSO_4$, have been used on fruits (Tiller and Merry, 1981; Chen et al., 1997). This finding is consistent with the factor identification results, which indicated that the main factors influencing the spatial distribution of Cu were not only industrial activity but also land use type. Therefore, the hotspots were distributed in areas with relatively higher industrial output values and lower industrial output values, which may be caused by other factors in addition to industrial activity.

4 Discussion

4.1 Soil heavy metal pollution and sources

Table 5 shows that results of an analysis of the characteristics of soil heavy metal pollution in Beijing. The soil As, Cd, and Ni contents were close to the soil background values in Beijing, which suggested that natural factors were important sources. However, in some local areas, their contents were also obviously affected by anthropogenic factors. Compared with the soil As, Cd, and Ni, the soil Cu, Pb, and Zn pollution in Beijing was more obvious and 22.03%, 14.98%, and 9.68% higher than the background values of Beijing, respectively, which showed that these metals were influenced by human activity. The factors affecting their content distributions were mainly anthropogenic factors, which were in accordance with the conclusions obtained in this study.

The factor analysis also corroborated the ranking results of influencing factors of heavy metals in Beijing. Zheng et al. (2008) used a factor analysis to analyze the sources of soil heavy metals in Beijing. The results showed that Cu, Pb, and Zn belonged to the first principal component and they were mainly affected by human activities. Ni and Cr belonged to the second principal component, which was mainly affected by natural factors, such as soil parent

Table 5 Assessment of soil heavy metal pollution in Beijing (n = 844)

Heavy metal	Heavy metal content (mg/kg)	Background value (mg/kg)	(Heavy metal content-Background value)/ Background value
As	7.18a	7.81a	–
Cd	0.150a	0.145a	3.45%
Cr	35.94a	31.1b	15.56%
Cu	24.04a	19.7b	22.03%
Ni	27.67a	27.9a	–
Pb	28.86a	25.1b	14.98%
Zn	65.37a	59.6b	9.68%

Note: Difference test was conducted between heavy metal content and the corresponding background value. Mean with different letters were significantly different ($p < 0.05$).

material. Xia et al. (2011) used a factor analysis to analyze the sources of urban soil heavy metals in Beijing. The main source of Cd, Cu, Pb, and Zn was man-made sources. Cr and Ni were affected by natural sources. These results were consistent with the conclusion in this study.

4.2 Main factors that influence soil heavy metal contents

In this study, soil parent material was an important factor affecting the heavy metal elements, indicating that it was one of the important sources of heavy metals in Beijing. The soil parent material strongly affected the geochemical characteristics of soils (Salonen and Korkka-Niemi, 2007). Parent material composition, especially sedimentary and volcanic parent materials, significantly influenced the heavy metal contents in most analyzed soils (Palumbo et al., 2000). Moreover, the heavy metal contents derived from different soil parent materials were significantly different. For example, the As content (44.5 mg/kg) in sedimentary limestone in China was 74 times higher than that in neutral igneous rock (0.6 mg/kg). The Cd content in sedimentary limestone (1.052 mg/kg) was 210 times higher than that in laterite parent material (0.005 mg/kg) (CNEMC, 1990). Nael et al. (2009) found that, compared with the soil forming process, the influence of soil parent material on heavy metal contents was more obvious. Previous studies also showed that Cr and Ni in Beijing were influenced by the soil parent material (Chen et al., 2005; Zheng et al., 2008), which was consistent with the research conclusions in this study.

Land use type was another important factor that affected the soil heavy metals in Beijing. Related research showed obvious differences in the heavy metal contents under different land use types. For example, Kuusisto-Hjort and Hjort (2013) found that metals were strongly correlated with the proportions of dense suburban land use and imperviousness in the Helsinki region, Finland. A previous study showed that Cd, Cu, Pb and Zn in classical garden in Beijing were obviously higher than those in the other land use types (Xia et al., 2011). Xu et al. (2016) studied soil heavy metals under different land use types in Beijing and found that the Cd, Cu and Zn contents in a greenhouse were significantly higher than that of other land use types, which were closely related to the high input of agricultural chemicals in greenhouse soil. Zheng et al. (2016) studied the coastal soils on Chongming Island in the Yangtze River Estuary and found that the soil heavy metals concentrations differed under different land use types. In paddy fields and dryland, the concentrations of Cr, Zn, Cu, Ni, and As were higher than those in forestland due to frequent cultivation.

Soil type was also a major factor that affected the distribution of soil heavy metals in Beijing. Different soil types were formed by the long-term weathering of different soil parent material (Mahmoodi et al., 2016). For different soil types, the soil clay minerals, oxides, and organic matter contents were different. Clay minerals are among the most popular adsorbents that immobilize heavy metals. They have many advantages, such as high abundance, great sorption capacity, and stable physical and chemical properties (Zhou et al., 2017). Previous study showed that the adsorption and desorption of heavy metals were associated with soil properties, including the pH and organic matter content (Zeng et al., 2011). Heavy metal translocation and accumulation also varied; therefore, the heavy metal contents in different soil types were obviously different. For example, Chen et al. (2002) studied the surface soil in Florida and found that the As content significantly varied in different soil types. Soil properties (clay, organic C) are important factors that affect the natural background concentration of As in Florida soils.

Industrial activity was also an important factor that affected the spatial distribution of soil heavy metals in Beijing. In this study, industrial activity had a significant influence on the soil Cu, Pb, and Zn. Many studies have shown that industrial activity has important effects on heavy metal contents and different industrial activities will lead to the accumulation and enrichment of different heavy metals. Each industrial activity is usually linked to some specific metals. For example, Pb, Ni, Cu, and Co are used as catalysts, modifiers, and dryers (Jan et al., 2010). Zn is usually linked to agrochemical production, such as fertilizers. Pb is usually associated with oil refinery activity, while Ni is often linked to petrochemical emissions (Duong and Lee, 2009). Generally, the exhaust gases, waste water, and solid waste generated by industrial activities will lead to the accumulation of soil heavy metals to distinct degrees.

Population density and traffic activity also had certain impacts on specific soil heavy metal contents. Previous study showed that heavy metals (Pb, Zn and Cu) were correlated well with population density (Al-Shayeb, 2003). In this study, population density is a factor affecting Pb content. Regions with high population density tend to have intensive human activities, which are the likely causes of soil heavy metal accumulation. In addition, traffic activity is also a main factor affecting the Cd content. Related research showed that Cd is closely related to the wear of automobile tires and combustion of fuel; therefore, traffic activity may lead to increased Cd contents (Ebqa'ai and Ibrahim, 2017).

Atmospheric deposition and sewage irrigation were also major factors that affected the distribution of soil heavy metals. The accumulation of Pb is closely related to atmospheric deposition. Atmospheric deposition is the main source of heavy metal accumulation in some areas (Engel-Di Mauro, 2018). Related studies show that heavy metals in atmospheric particulates are much higher than those in soil (Hu et al., 2018). In this study, early monitoring data of the atmospheric deposition was truly hard to obtain; therefore, this factor was not included in the regression equation, which would have a certain influence on the final result. In addition, sewage irrigation is usually an important factor that leads to the accumulation of soil heavy metals (Liu et al., 2005; Yang et al., 2008). However, in this study, sewage irrigation was not the main factor affecting soil heavy metals in Beijing, which may be mainly related to the research scale (Yang et al., 2008). From the whole research area, the influence scope of sewage irrigation was relatively small. Therefore, the effect of sewage irrigation on soil heavy metal contents in Beijing was not obvious.

4.3 Influence of factor interaction on soil heavy metal contents

The interaction of factors significantly affected the spatial distribution of soil heavy metals. In general, regions with more intensive industrial activities will have a larger labor force demand; therefore the population density will usually be high. The demand for transportation of industrial products enhances the traffic conditions in these areas. Industrial activities will produce more wastewater, which can easily lead to high contents of heavy metals in rivers, and if the polluted water is used for irrigation, then heavy metals will accumulate in soil (Chen et al., 2016; Turan et al., 2018). Therefore, interactions between industrial activity and population density, sewage irrigation and traffic activity had an obvious influence on Cd, Pb and Zn. The interaction between land use type and traffic activity also had an obvious influence on soil Cd, Pb and Zn, which may be related to the importance of traffic activity as a driving factor of land use type. For example, a previous study showed that transportation factors (including the distance to the expressway and the main road) contributed nearly 30 percent of the importance for industrial land use changes (Zhang et al., 2018a). In addition, the interaction between soil parent material and soil type had an obvious influence on Cd, which may be related to the formation of different soil types by the long-term weathering of different soil parent material (Daher et al., 2019).

4.4 Main feature of this method

CATREG can be a potential method for identifying factors that influence soil heavy metals. When we use factor analysis, the final result is deduced mainly from prior knowledge (Dragović and Mihailović, 2009). Spatial overlay analysis is often used in the geostatistics and pollution sources are usually from qualitative speculation (Wang and Lu, 2011). Geographical detector is based on the spatial variability of geographic variables, but we should subjectively sort out the degree of variation of environmental variables (Luo et al., 2019; Qiao et al., 2019). Compared with the factor analysis method, geostatistical approaches, and the geographical detector tool (Table 6), the data adopted in this study can be both categorical and numerical variables. Moreover, prior knowledge was not needed to classify the environmental data and the influence of environmental factors on soil heavy metal contents was objectively analyzed. The main factors affecting soil heavy metals were identified and the degree of influence of different environmental factors on soil heavy metal contents was also ranked. The effects of environmental factors on soil heavy metals were semi-quantified. This method identified the effects of various environmental factors on soil heavy metal elements and overcame the limitation of the stable isotope tracer method, which cannot identify multiple sources.

However, when we use this method, we should pay attention to the following factors. First, the final result is close to the influencing factor data, and if we want to generate more accurate results, we should obtain more complete influencing factor data. Second, the sources of soil heavy metals may overlap, such as industrial activity and sewage irrigation. When the data analysis did indeed show multicollinearity, a further statistical analysis (PCA and CA) should be conducted to reduce multidimensional data sets to lower dimensions (Davis et al., 2009; Kim et al., 2012). However, as for the regression equations in this study, all the tolerance values were greater than 0.6, which suggested that there were no significant multicollinearity problems (Michailidis et al., 2011). Finally, because we cannot obtain all the influencing factor data, certain differences will occur between the final result and actual situation. However, compared with previous studies, the main influencing factors of soil heavy metals could be accurately identified by this method.

5 Conclusions

The soil parent material, land use type, soil type and industrial activities were the main factors that influenced the spatial distribution of soil heavy metals in Beijing. The soil parent material, soil type, and land use type significantly affected the spatial distribution of soil As,

Table 6 Comparison of different identification methods

Method	Characteristic	Limitation
Factor analysis	Using fewer factors to represent many primitive variables, data dimensionality reduction is realized, and factor variables are more interpretable by rotation.	Meaning of factor cannot be completely determined, there is a lack of information, and conclusions are mainly speculative.
Geostatistics	The spatial distribution and variation of target elements can be seen intuitively by considering both numerical and spatial location (Journel and Huijbregts, 1978).	Limited to map overlay, lack of objective data, and pollution sources are from qualitative speculation.
Stable isotope tracer	Main sources of soil pollutants are objectively, accurately, and quantitatively estimated (Zhang et al., 2018b).	It cannot identify more than three kinds of pollution sources.
Geographical detector	Both qualitative and quantitative data are available, and factor interaction can be analyzed by this method.	Data must be transformed to categorical data. Data classification is based on prior knowledge, and subjectivity is strong. Different classifications will result in different conclusions.
This method	It can handle not only categorical data but also process numerical data. It can objectively and quantitatively identify the effects of various factors on heavy metals.	There is a need for a certain amount of sample data.

Cd, Cr, Cu, Ni, Pb and Zn. In addition, the soil Cd, Cu, Pb, and Zn were influenced by anthropogenic factors, such as industrial activity. Pb and Zn were also influenced by population density. The interactions between industrial activity and other factors (population density, sewage irrigation and traffic activity), between land use type and traffic activity, and between soil parent material and soil type significantly affected the spatial distribution of soil As, Cd, Pb, and Zn. On the basis of existing methods, this method assigned environmental factors to soil heavy metal data, objectively identified the influence of various environmental factors on soil heavy metal contents by using CATREG, and semi-quantified the influence of environmental factors on soil heavy metal contents.

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