



Assessment of Heavy Metal Pollution in Soil and Classification of Pollution Risk Management and Control Zones in the Industrial Developed City

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Abstract

Soil heavy metal pollution threatens ecological health and food security. It is significant to classify pollution risk management and control zones, which can effectively cope with soil pollution and scientifically carry out soil remediation projects. In this study, based on 665 soil samples collecting from Ningbo (southeast China), single pollution index and Nemerow composite pollution index (NCPI) were measured to assess soil pollution risk, and self-organization mapping model was applied to classify management and control zones. Results showed that the heavy metal pollution in the northwest part was more serious, while the east part was less polluted. Although more than 75% soil samples had negligible risks, the Hg and Cu pollution was greatly influential and notable as their polluted samples accounted for 24.21% and 12.48% respectively. Moreover, about 55.34% soil samples and more than half study region had pollution grades, and NCPI values were obviously high with the center of northwest study area. Results also showed that the study region could be classified into four zones with good spatial variabilities. Specifically, Monitored Zone with High-risk Pollution had the highest NCPI caused by human activities, while Controlled Zone with Severe Pollution had relatively high NCPI caused by industrial and agricultural production. Protected Zone with Ecological Conservation and Restricted Zone with Potential Pollution had low NCPIs attributing to historical or natural factors. Our study implies that the classified zones can provide fundamental and momentous information for establishing appropriate priorities of heavy metal risk management and control.

Keywords Heavy metal · Soil pollution assessment · Risk management and control · SOM

Introduction

With the fast development of urbanization and industrialization, the rapid growth of Chinese economy has accelerated the resource consumption and the ecological environment deterioration (Wang et al. 2019). Such situation poses a great threat to the soil environment, one of which is the severe heavy metal pollution. According to a

national survey of soil pollution in China, the overall soil environmental pollution was noteworthy. The heavy metal concentrations of 19.4% soil samples collected from agricultural land were higher than the maximum safe concentration, and more than 23 million hectares of agricultural land were polluted by heavy metals (NSPCIR 2014). Apart from damaging the soil quality, the heavy metals in soil can not only deteriorate underground water and atmospheric environment, but also lead to decreased food production and unhealthy agricultural products (D'Emilio et al. 2013). At present, soil heavy metal pollution has become increasingly prominent and widespread in China. Cd is determined as one of the priority control heavy metals, whose pollution is the most serious in Guangxi Province, Zhejiang Province, and Guangdong Province (Sun et al. 2020). Industrial regions particularly mining areas are more severely polluted by heavy metals than agricultural regions, and those in the southeast China are severer than those in the northwest China (Yang et al. 2018). And the natural source,

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atmospheric deposition, industrial activities, and agricultural inputs are major pollution sources of heavy metals (Liang et al. 2017). As a whole, the heavy metal pollution in soil has expanded from local to region, from single pollution to compound pollution, from point source pollution to non-point source pollution.

In an effort to availablely control serious soil heavy metal pollution and monitor soil environmental quality, Chinese government has already implemented many soil environment protection policies. For instance, the *Arrangement of Soil Environmental Protection and Comprehensive Management* in 2013 required governments to take responsibilities to determine priority protection areas and rank soil environmental qualities (State Council of PRC 2013). And the *Action Plan for the Prevention and Control of Soil Pollution* in 2016 asked for classification managements to ensure the safety of agricultural products (State Council of PRC 2016). Under this circumstance, numerous work has been done about soil heavy metal pollution, including sampling points design (Chu et al. 2010; Li et al. 2016), pollution sources analysis (Keshavarzi and Kumar 2019; Lü et al. 2018), pollution risks assessment (Huang et al. 2018; Zang et al. 2017). To be specific, single factor, Nemerow, and geo-accumulation indexes were commonly applied to comprehensively assess the level of heavy metal pollution (Zhang et al. 2018). Likewise, the Hakanson ecological risk index and USEPA model were widely applied to assess the potential ecological risk and human health risk in Soil-Plant-Human System (Pan et al. 2016). However, these efforts mainly focused on the spatial pattern and pollution assessment of soil heavy metals (Marrugo-Negrete et al. 2017; Mu et al. 2019), while few can further take the pollution management and control into consideration.

It is of vital significance to manage and control heavy metal pollution in soil. Classifying risk management and control zones can determine the priority for integrated management and then put forward targeted strategies, which plays a fundamental role for the regional pollution risk control of heavy metals in soil (Chen et al. 2014). Related studies established an evaluation and zoning method for risk control based on heavy metal pollution grade of agricultural land (Wei et al. 2018). Aiming at polluted areas with high background value of heavy metals, a systematical approach of ecological risk evaluation and classification was conducted (Yu and Wu 2018). In addition, some spatial technologies, such as geographic methods and clustering methods, were effectively applied to improve spatio-temporal zoning of soil environmental functions (Jia et al. 2015). Nevertheless, those existing studies mainly concentrated on the zoning theories and methods rather than empirical researches.

Although a few previous studies carried out risk management and control for heavy metals based on soil

pollution assessment, the data sources were spatially single continuous variables that were mainly measured data of heavy metals in soil. And the mostly used methods were spatial interpolation or multivariate statistics. Moreover, the classified management and control zones might be not workable and actionable in a county where administrative units were the basic management units. In this study, we selected a typical industrial city in southeast China as the case study area and collected 665 soil samples in order to measure the contents of eight soil heavy metals and assess the pollution risk of soil heavy metals. Based on SOM model, the assessment results were combined with multi-source data (i.e., discrete natural, socio-economic and environmental variables) relating to heavy metal pollution and accumulation to classify different pollution risk management and control zones. Therefore, the research goal is to classify reasonable and practical zones based on collected multi-source discrete data. And specific aims are to explore: (i) what is the current status of soil heavy metals, (ii) how to assess heavy metal pollution in soil, and (iii) how to classify pollution risk management and control zones.

Materials and Methods

Study Region

The study area is Ningbo city in Zhejiang province, which is located in the south of Yangtze River Delta, southeast China (Fig. 1). It covers six districts including Jiangbei District, Zhenhai District, Haishu District, Jiangdong District, Yinzhou District, and Beilun District. Ningbo city has diverse soil types, dense roads and rivers, and abundant resources. Besides, there are ~85 minerals in Ningbo city, including eight metal minerals (e.g., Pb, Cu, Fe, and Ag) (Liu et al. 2016; You 2017). Ningbo city has well-developed petrochemical, electronic, metallurgy, building materials, and textile industries. In recent years, however, along with the rapid economic development, the environmental pollution has become increasingly serious. Particularly, soil heavy metal pollution caused by industrial wastes from polluting enterprises had a significant impact on soil quality, crop safety, and lives of local residents (Li et al. 2018; Liu and Borthwick 2011). Thus, it is necessary to identify the pollution risk in soil to protect and improve the soil environment.

Data

We collected multi-source data, including soil samples, remote sensing images, land-use data, statistics, and meteorological data, for the year 2013. Landsat TM images for calculating Normalized Difference Vegetation Index

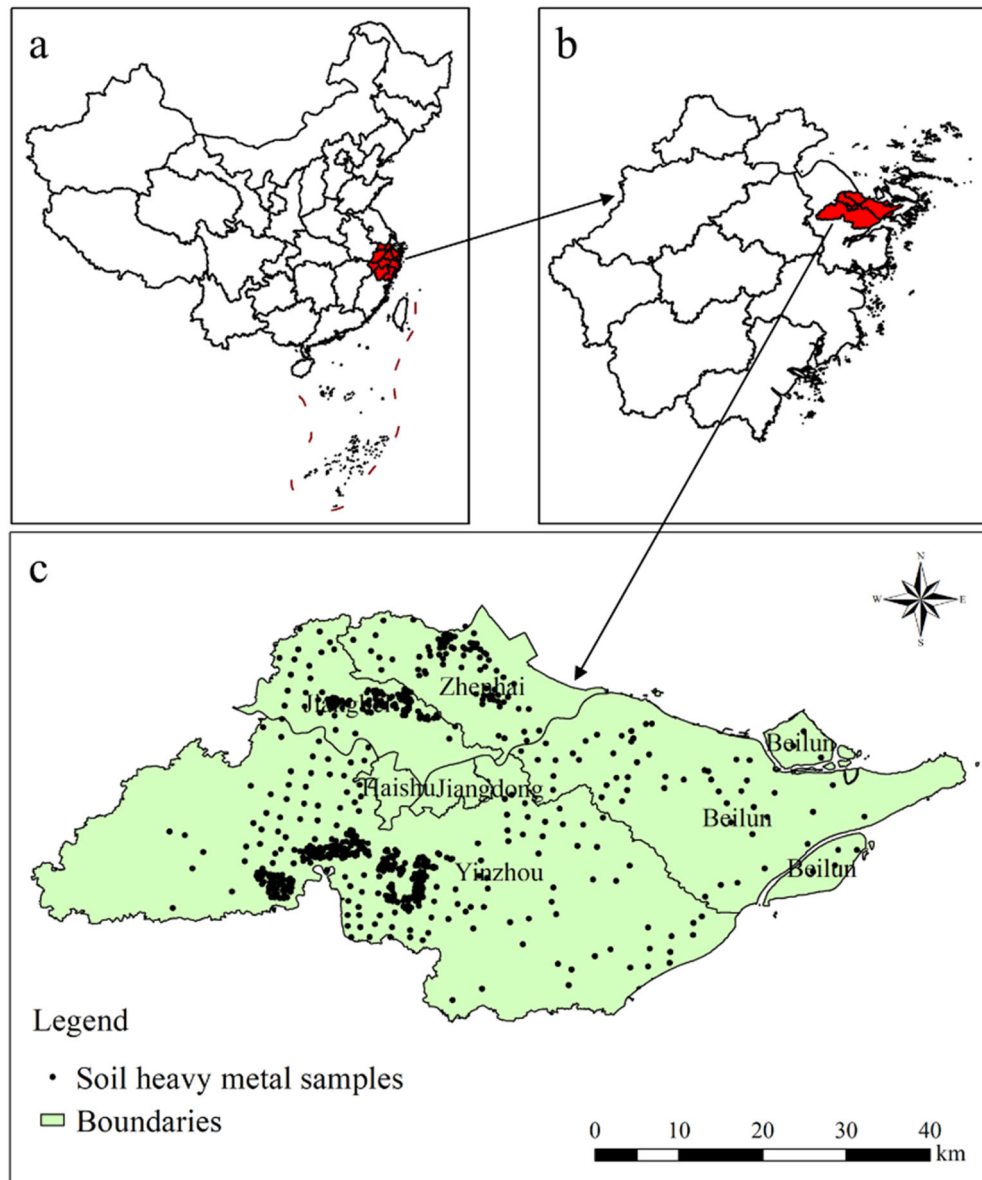


Fig. 1 The specific location of the study region and spatial distribution of soil heavy metal samples

(NDVI) were acquired from the USGS website (<http://earthexplorer.usgs.gov/>). The digital elevation model (DEM) data were derived from Geospatial Data Cloud (<http://www.gscloud.cn/search>), which provided terrain elevation and slope information. The road areas and water body areas were obtained from land-use map provided by Ningbo Bureau of Natural Resources and Planning. The population data were derived from Ningbo Statistical Yearbook. The input data of fertilizer (i.e., nitrogenous fertilizer, phosphatic fertilizer, potassic fertilizer, compound fertilizer, and organic fertilizer) and pesticide were derived from Ningbo Soil Heavy Metal Pollution Investigation. Precipitation data were acquired from National Meteorological Information Center (<http://data.cma.cn/>). The polluting enterprise data

were acquired from the Ministry of Environmental Protection Data Center (<http://datacenter.mep.gov.cn/>).

We collected a total of 665 soil samples using systematic grid sampling from the study region. Each soil sample was combined with five subsamples collected from five locations within five meters. Besides, in order to collect more representative samples, we increased partial sampling density based on local features. All soil subsamples were collected at a depth of 0–20 cm with a stainless-steel shovel and their coordinates were recorded with a differential global positioning system (GPS) (Fig. 1). After collection, we air-dried all soil samples in the lab for several days at ambient temperature and passed them through a 2-mm nylon sieve for soil properties analysis. Afterward, we

ground some soil samples to pass through 100 meshes and stored them in closed polyethylene bags for heavy metal content analysis. To be specific, according to the agricultural sector standard (NY/T 1377-2007) of the People's Republic of China, soil pH was measured in H₂O with a soil/solution ratio of 1:2.5 (m/v) using the Glass Electrode method (GL, pHS-3C, REX, Shanghai, China). Total concentrations of Cr, Pb, As, Cu, Zn, and Ni in soil samples were acid-digested with HCl-HNO₃-HClO₄ and analyzed by the inductively coupled plasma optical emission spectrometry (ICP-OES 6300, Thermo Fisher Scientific, Waltham, MA, USA). Total Cd in soil samples were digested by HF-HNO₃-HClO₄ and analyzed by the inductively coupled plasma mass spectrometer (ICP-MS, Agilent 7500a, Palo Alto, CA, USA). Total Hg in soil samples were digested by HNO₃-HCl in a water bath and analyzed by the double channel atomic fluorescence spectrometer. In addition, we applied reagent blanks and standard reference materials for quality assurance and quality control. And the recovery rates of heavy metal elements were from 90 to 110% (Hu et al. 2017).

Methods

We first described the current status of soil pollution of eight heavy metals (i.e., Cr, Pb, Cd, Hg, As, Cu, Zn, and Ni). A series of statistical indexes (i.e., min, max, mean, median, standard deviation, coefficient of variation, skewness, and kurtosis) were applied to analyze soil heavy metal characteristics. Based on the variogram calculation, kriging interpolation method and inverse distance weighted method were applied to obtain spatially continuous data based on discrete soil sample data. Subsequently, we applied single-factor evaluation and comprehensive pollution evaluation to assess heavy metal pollution of soil samples. Finally, we applied self-organization mapping (SOM) model to classify pollution risk management and control zones of soil heavy metals. Eleven socio-environmental indicators were selected as the potential heavy metal pollution sources. One-way variance analysis was applied to evaluate whether the classified management and control zones could be used to characterize spatial variability of soil heavy metals.

Single-factor evaluation

Single-factor evaluation is to classify heavy metal pollution risk and assess soil environmental quality based on relationships among screening values and intervention values of soil pollution risk in agricultural land and actual heavy metal contents in soil. When the content of a soil heavy metal in agricultural land is equal to or lower than its screening value of soil pollution risk, the risk to the quality and safety of agricultural products, crop growth, and soil

ecological environment is low, which can be ignored in general. Otherwise, the risk is high. Under this circumstance, it is indispensable to strengthen the monitoring of soil environment and agricultural products as well as take measures for soil remediation to ensure safety utilization. When the content of a heavy metal in agricultural land soil is higher than its intervention value of soil pollution risk, agricultural products are substandard, and agricultural land pollution risk is high, which should be taken strict control measures.

According to the Standards (Ministry of Ecology and Environmental of PRC 2018), five kinds of heavy metals (i.e., Cd, Hg, As, Pb and Cr) have screening values (S_i) and intervention values (I_i) at different pH values. Combining with soil heavy metal contents (C_i), we can evaluate soil pollution risk in agricultural land and divide soil environmental quality into three grades, i.e., Priority Protection I ($C_i \leq S_i$), Safety Use II ($S_i < C_i \leq I_i$) and Seriously Control III ($C_i > I_i$). Likewise, since the other three kinds of heavy metals (i.e., Cu, Ni, and Zn) only have screening values (S_i) at different pH values, combining with soil heavy metal contents (C_i), we can divide soil environmental quality into two grades, i.e., Priority Protection I ($C_i \leq S_i$) and Safety Use II ($C_i > I_i$). The agricultural land in Priority Protection I has negligible risk or even no risk, and the agricultural land in Safety Use II may have soil pollution with controllable risk, while the agricultural land in Seriously Control III has high soil pollution risk.

Comprehensive pollution evaluation

Comprehensive pollution evaluation, which is represented by Nemerow composite pollution index (NCPI), is applied to comprehensively analyze and evaluate soil heavy metal pollution based on maximum and average values of single pollution index (SPI) of eight soil heavy metals (Hu et al. 2017). Since NCPI takes the maximum value of SPI into consideration, the effect of most influential heavy metal cannot be smoothed. For a certain soil heavy metal sample, SPI and NCPI are calculated as follows:

$$SPI_i = \frac{C_i}{S_i} \quad (1)$$

$$NCPI_i = \sqrt{\frac{(SPI_{i\max})^2 + (\overline{SPI}_i)^2}{2}} \quad (2)$$

where i is a kind of heavy metal pollutant, SPI_i is SPI of pollutant i , C_i is the measured concentration of pollutant i , S_i is the evaluation standard of pollutant i (i.e., screening value), $NCPI_i$ is NCPI of pollutant i , $SPI_{i\max}$ is the maximum SPI, \overline{SPI}_i is the average SPI of eight heavy metals. According to evaluation standards, SPIs of different

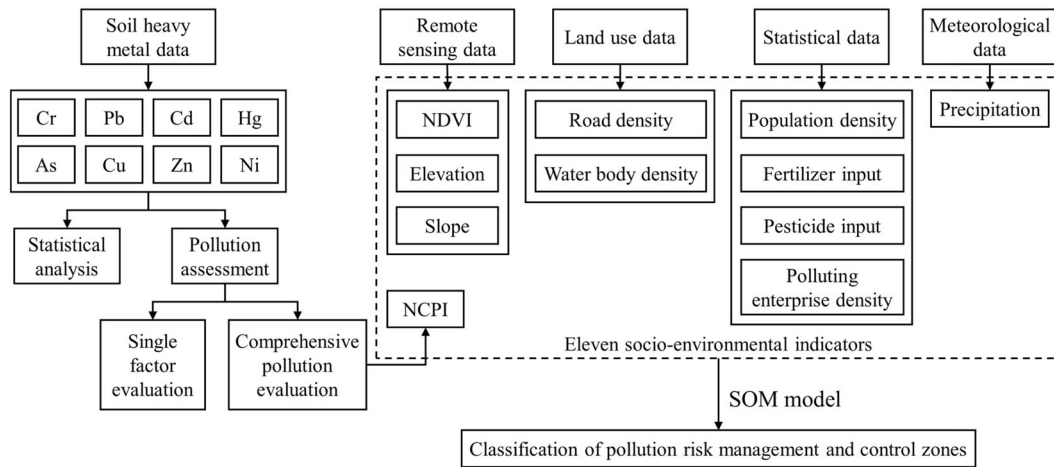


Fig. 2 The flowchart of the research

ranges can be divided into five grades, i.e., Safety ($SPI \leq 1.0$), Slight pollution ($1.0 < SPI \leq 2.0$), Mild pollution ($2.0 < SPI \leq 3.0$), Moderate pollution ($3.0 < SPI \leq 5.0$) and Severe pollution ($SPI > 5.0$). Likewise, NCPIs of different ranges can also be divided into five grades, i.e., Safety ($NCPI \leq 0.7$, indicating clean surroundings), Alert ($0.7 < NCPI \leq 1.0$, indicating slightly clean surroundings), Mild pollution ($1.0 < NCPI \leq 2.0$, indicating pollutants exceed background and soils start to be polluted), Moderate pollution ($2.0 < NCPI \leq 3.0$, indicating soils have been polluted moderately), and Severe pollution ($NCPI > 3.0$, indicating soils have been polluted severely) (Fig. 2).

SOM model

SOM neural network is an unsupervised learning algorithm that can simulate the self-organization mapping function of the human brain’s nervous system. It extracts important characteristics of input data and then classifies them into several categories on the basis of similarity factors. The SOM network can reduce original complex high-dimensional data to low-dimensional data (e.g., a two-dimensional network of neurons) without changing the topological structure (Kohonen 1990, 2006, 2013).

SOM model consists of two parts: one is the input layer accepting external input data, and the other is the output layer (or competitive layer) arranged in a two-dimensional structure (Fig. 3). Each input neuron is linked to each output neuron, which achieves a full connectivity between the two layers. We assume to input an n -dimensional vector $X = (x_1, x_2, x_3, \dots, x_n)$ with n neurons and output a two-dimensional network with m neurons ($n < m$). Each input neuron i has a two-dimensional feature vector $X(i) = (X_1(i), X_2(i), X_3(i), \dots, X_n(i))^T$. We take W_{ij} ($i = 1, 2, 3, \dots, n; j = 1, 2, 3, \dots, m$) as the connection weight between the i th input neuron and the j th output neuron. And we set the percentages of input

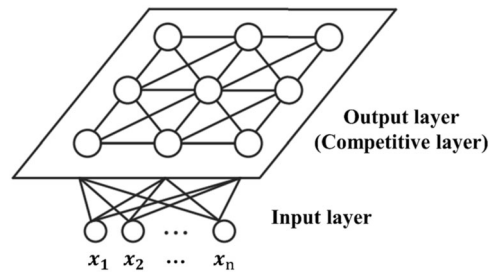


Fig. 3 SOM neural network

data used for training and test were 70 and 30%. The process of neural network algorithm training works as follows:

Step 1: Initialization. Initialize the weight with a small random value in the interval $[0, 1]$. We set the initial learning efficiency as $\eta_{(0)}$, the initial area as $N_{g(0)}$, and normalize all of the input vector X and the weight vector W_j . Equations are

$$X' = \frac{X}{\bar{X}} \tag{3}$$

$$W'_j = \frac{W_j}{\bar{W}_j} \tag{4}$$

$$\text{Here, } X = \left(\sum_{j=1}^m (x_j)^2 \right)^{\frac{1}{2}}, W_j = \left(\sum_{i=1, j=1}^n [W_{ij}(0)]^2 \right)^{\frac{1}{2}}.$$

Step 2: Competition. As different discriminant function values correspond to the calculation of neurons of different input neurons, competition occurs. The winner of the discriminant function is selected as the competition winner. Euclidean distance is used as the discriminant function and calculated as

$$d_j = \left[\sum_{j=1}^m (X'_i - W'_j)^2 \right]^{\frac{1}{2}} \tag{5}$$

Step 3: Cooperation. Find the minimum distance and determine the winning neuron g through competitive learning. Find the domain through the winning neuron to achieve cooperation between adjacent neurons:

$$d_m = \min[d_j] \quad (6)$$

Step 4: Adaptation. Iterate and adjust the connection weight. The vectors connected by the winning neuron and all neurons in winning neighborhood are adjusted to near the input vector at varying degrees that depend on the distances between neighborhood neurons and the winning neuron. And then obtain a new learning rate $\eta_{(t)}$ and new domain $Ng_{(t)}$.

$$W_j(t+1) = W_j(n) + \eta_{(t)} \cdot |X'_t - W'_j| \quad (7)$$

$$\eta_{(t)} = \eta_{(0)} \cdot (1 - T^{-1}) \quad (8)$$

$$Ng_{(t)} = \text{int}[Ng_{(0)} \cdot T^{-1}] \quad (9)$$

Here, $j \in Ng_{(t)}$ ($0 < \eta_{(t)} < 1$), j , t is the number of archived iterations, and T is the total number of iterations. When T reaches 2000, the result of SOM model remains stable.

In this process, set $t = t + 1$. Repeat from Step 1 to Step 4 until $t = T$.

In the present study, we established a series of socio-environmental indicators for SOM model to realize classification. There are masses of factors influencing soil heavy metal, such as soil parent material, atmospheric deposition, sewage irrigation, agricultural fertilizer and pesticide input, road density, mineral exploration, polluting enterprise emission, etc. On account of different sources of soil heavy metals, the contributions of heavy metals vary from one pollution source to another (Cheng et al. 2014; Wang et al. 2014; Zhang et al. 2012). The distribution of heavy metals in the crust is the direct cause of geogenic pollution, and soil parent material contributes significantly to Cr and Ni (Zheng et al. 2002). Atmospheric deposition, which can bring heavy metals into soil from human activities like daily life and agricultural input, has a great contribution to Cd (Zeng et al. 2015). Urban and industrial wastewater are discharged into rivers and soil, and sewage irrigation contributes a lot to Ni (Wang et al. 2014). A great deal of pesticide, fertilizer, and agricultural film in intensive agriculture can cause excessive heavy metals in soil, and agricultural fertilizer and pesticide input have almost the same contribution to heavy metals. Since the burning of leaded petrol and wear of automobile tires can lead to heavy metal pollution in soil and dust, road density contributes greatly to Pb (Zheng et al. 2002). Since the discharge of three industrial wastes can cause compound pollution of multiple heavy metals, mineral exploration and metal smelting

contribute largely to As, Ni, Zn, Cr (Gao and Ji 2018). The soil heavy metal content around industrial land is high and is closely related to the distance of polluting enterprises, and polluting enterprise emission has a significant contribution to Ni, Zn, Cr (Kim et al. 2019).

As a consequence, eleven socio-environmental indicators (i.e., NDVI, elevation, slope, NCPI, road density, water body density, population density, fertilizer input, pesticide input, precipitation, and polluting enterprise density) were selected as the potential pollution impact factors. Due to different physical meanings and units of these socio-environmental indicators, their order of magnitude has great differences. In order to eliminate dimensional influence among indicators, we applied the standardization method to normalize the eleven indicators. The specific formula is:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (10)$$

where x' is the standardized value, x is the actual value, x_{\min} is the minimum value within each indicator, while x_{\max} is the maximum value within each indicator

Results and Discussion

Descriptive Statistics of Soil Heavy Metals and the Spatial Distribution

There were 665 samples of eight soil heavy metals respectively (Table 1). Although the content ranges of eight heavy metals varied greatly, their maximum values were all far more than soil background values of both Zhejiang province and China. Particularly, the contents of Hg, Cd, and Cu varied in a wide range with the maximum being about 34 times, 15 times, and 9 times of the minimum respectively. Except for As, both mean and median values of the other seven heavy metals all exceeded the corresponding two kinds of background values. Taking soil background values of Zhejiang province as the standard, the mean values of Cr, Pb, Cd, Hg, Cu, Zn, and Ni were 1.5 times, 2.2 times, 3 times, 6 times, 2.3 times, 1.7 times, and 1.3 times of their corresponding soil background values respectively. In terms of CV, there were no weak or highly variations among the eight heavy metals in the study region. And the eight heavy metals were ranked from high variation degree to low variation degree as Hg, Cd, Cu, Zn, Pb, Cr, As, and Ni. In addition, the skewness of all heavy metals was positive except Ni. And the kurtosis distributions of Zn, Pb, Cr, Cd, Cu, and As were concentrated to show a peak, while Hg and Ni were scattered with a flat distribution.

After logarithmic transformation of whole samples, Pb was normally distributed. After BOX-COX transformation

Table 1 Statistical analysis of eight heavy metals (number of samples is 665)

Heavy metals	Min	Max	Mean	Median	SD	CV	Skewness	Kurtosis	SBV-Zhejiang	SBV-China
Cr	19.90	148.40	79.95	84.40	20.26	25.34	-0.70	1.36	52.90	61.00
Pb	25.00	98.30	51.43	50.20	12.87	25.02	0.85	1.31	23.70	26.00
Cd	0.03	0.46	0.21	0.20	0.07	35.47	1.15	1.94	0.07	0.10
Hg	0.05	1.71	0.54	0.43	0.38	69.06	1.06	0.65	0.09	0.07
As	1.76	13.20	7.21	7.15	1.89	26.24	0.38	0.75	9.20	11.20
Cu	8.92	78.90	39.91	38.70	11.52	28.86	0.76	1.72	17.60	22.60
Zn	44.40	240.00	122.62	116.00	28.71	23.42	1.43	3.41	70.60	74.20
Ni	8.09	55.80	32.13	33.50	8.55	26.63	-0.62	0.65	24.60	26.90

SBV represented soil background value (National Environmental Monitoring Center of the People's Republic of China 1990). The unit of CV was % and units of others were mg/kg

Table 2 The variogram parameters of heavy metals

Heavy metals	Model	Nugget	Still	Range	Aeolotropism	Nugget/still ratio
Pb	Exponential	0.040	0.041	0.793	Exist	0.962
Cd	Gaussian	0.002	0.004	0.425	Exist	0.478
Hg	Spherical	0.026	0.130	0.106	Exist	0.197
As	Gaussian	3.639	9.055	0.460	Exist	0.402
Cu	Gaussian	57.615	68.199	0.090	Exist	0.845
Zn	Spherical	196.760	686.020	0.308	Exist	0.287
Ni	Gaussian	31.605	83.548	0.379	Exist	0.378

of the rest heavy metals, Cd, Hg, As, Cu, Zn, and Ni were normally distributed except Cr. Therefore, the inverse distance weighted method was used to interpolate Cr, and the kriging method was used to interpolate other heavy metals. According to variogram parameters (Table 2), nugget values were all greater than zero, indicating the random variation caused by experimental errors. Hg had strong spatial autocorrelation (nugget/still ratio was <0.25) with mainly structural variation affected by natural factors. As and Ni had moderate spatial autocorrelation (nugget/still ratios were between 0.25 and 0.75), whose spatial variations were structural variation and random variation affected by both natural factors and human factors. Since the nugget/still ratios of the rest heavy metals were greater than 0.75, their spatial variations were mainly random variation and orders of human influences were ranked as Zn > Cd > Pb > Cu.

Spatially, the heavy metal pollution in southeast Zhenhai district and the junction of Haishu, Jiangbei, Jiangdong, and Yinzhou districts was more serious, while Beilun district and west Yinzhou district were less polluted (Fig. 4). First of all, the core areas of Cr with high values were Haishu district and southeast Zhenhai district. The content of Cr spread from core to periphery with a decreasing trend, while other areas had relatively low Cr content. As to Pb, the high-value area was located at southeast Yinzhou district and the boundary of Haishu and Yinzhou district. Likewise, the content of Pb spread from high-value center to

surrounding areas with a decreasing trend and Beilun district had relatively low pollution. Differently, the Cd pollution was generally high with a banded distribution. The southwest corner of Yinzhou district was the Cd high-value center and decreased to the northeast. And the boundary of Yinzhou and Beilun district was another high-value center. As to Hg, the junction of Haishu, Jiangbei, Jaingdong, and Yinzhou districts was the core area of high value, which was similar to Pb. The content of Hg decreased from core to periphery and reached low-value area in the southeast where Beilun district had the lowest pollution. The As intensively concentrated in southeast Zhenhai district and southeast margin of Yinzhou and Beilun districts, while west Yinzhou district had very low As content. The high-value areas of Cu were discrete, which were mainly located in middle Yinzhou district, west Beilun district and the junction of Yinzhou, Jiangbei, and Haishu districts. The content of Cu was generally high and decreased from high-value areas to the southwest. The content of Zn was also generally high, but it showed a banded continuous distribution and crossed the whole study region. High-value areas were distributed in Haishu district and north Yinzhou district, while only a small part in southeast Beilun district had low value. As to Ni, high-value areas were distributed in Haishu district, Jiangdong district, south Zhenhai district, southeast margin of Yinzhou and Beilun districts, while low-value areas were distributed in southeast corner of study region.

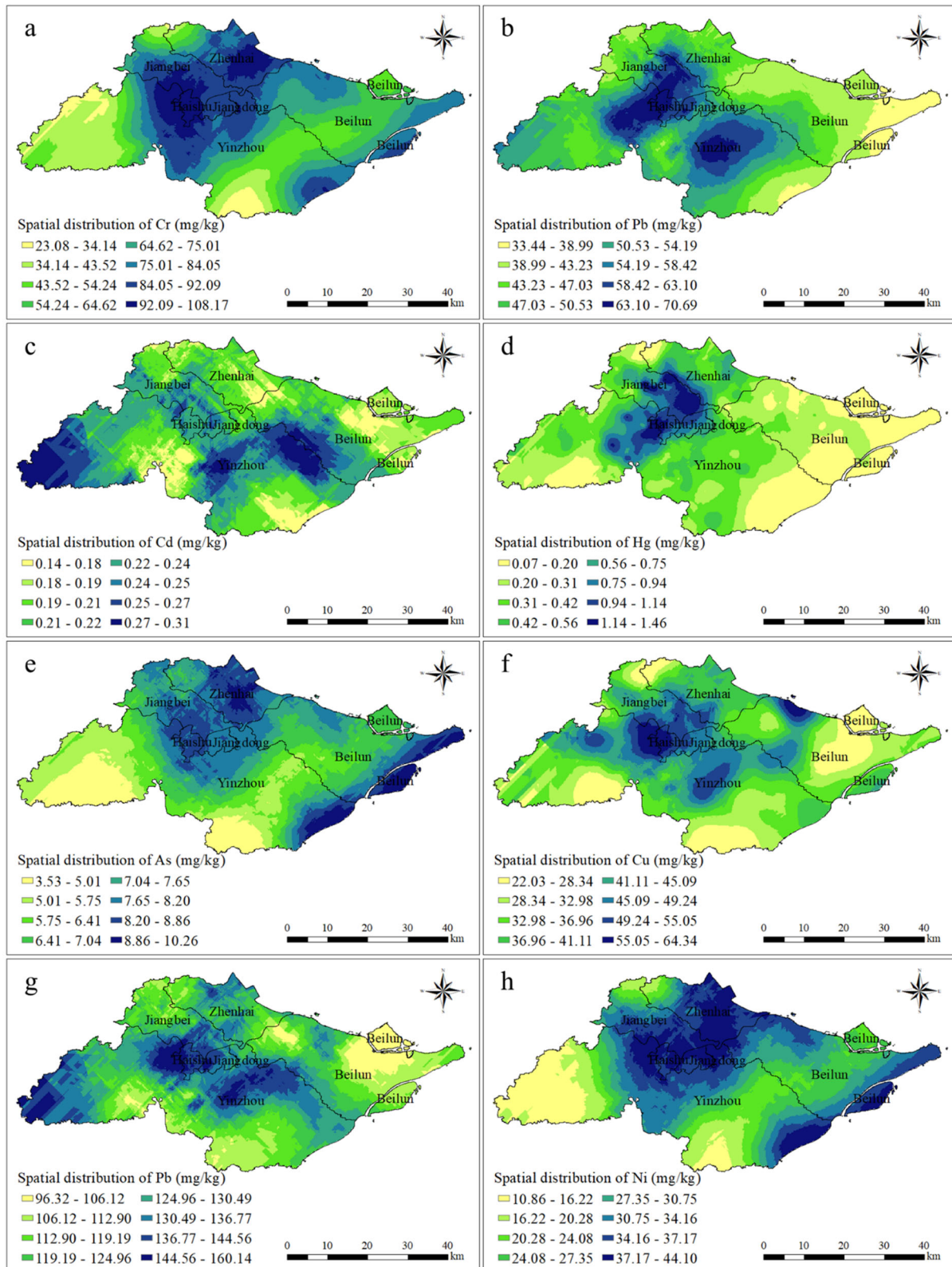


Fig. 4 The spatial distribution of eight soil heavy metal contents, i.e., **a** Cr, **b** Pb, **c** Cd, **d** Hg, **e** As, **f** Cu, **g** Zn, **h** Ni

Table 3 Soil pollution risk evaluations and grades of eight heavy metals

Heavy metals	Number of samples	Priority Protection I		Safety Use II		Seriously Control III	
		Number	Proportion (%)	Number	Proportion (%)	Number	Proportion (%)
Cr	665	665	100.00	0	0.00	0	0.00
Pb	665	636	95.64	29	4.36	0	0.00
Cd	665	616	92.63	49	7.37	0	0.00
Hg	665	504	75.79	161	24.21	0	0.00
As	665	665	100.00	0	0.00	0	0.00
Cu	665	579	87.07	86	12.93	–	–
Zn	665	651	97.89	14	2.11	–	–
Ni	665	665	100.00	0	0.00	–	–

Table 4 Pollution grade proportions of SPIs of eight heavy metals (Number of samples is 665)

Heavy metals	Safety	Slight pollution	Mild pollution	Moderate pollution	Severe pollution	Number of polluted samples	Proportion of polluted samples
Cr	100.00	0.00	0.00	0.00	0.00	0	0.00
Pb	95.64	4.36	0.00	0.00	0.00	29	4.36
Cd	92.63	7.37	0.00	0.00	0.00	49	7.37
Hg	75.79	16.54	5.71	1.95	0.00	161	24.21
As	100.00	0.00	0.00	0.00	0.00	0	0.00
Cu	87.52	12.48	0.00	0.00	0.00	83	12.48
Zn	97.89	2.11	0.00	0.00	0.00	14	2.11
Ni	100.00	0.00	0.00	0.00	0.00	0	0.00

Except “Number of polluted samples”, the units were %

Assessment of Heavy Metal Pollution in Soil

From the perspective of single-factor evaluation results, a majority of heavy metal samples were in Priority Protection I (i.e., negligible risk or even no risk) and only a small proportion of samples were in Safety Use II (i.e., controllable risk), while no sample was in Seriously Control III (i.e., high risk) (Table 3). All the samples of Cr, As and Ni were in Priority Protection I. Most samples of Pb were in Priority Protection I with proportion of 95.64%, while 4.36% Pb samples were in Safety Use II. Similarly, the proportions of Cd samples in Priority Protection I and Safety Use II were 92.63 and 7.37% respectively. As to Hg, most samples were in Priority Protection I, accounting for 75.79%. The proportion of Hg samples in Safety Use II was 24.21% and the number of samples increased compared with Pb and Cd. The proportions of Cu samples in Priority Protection I and Safety Use II were 87.07 and 12.93% respectively. Analogously, most samples of Zn were in Priority Protection I with proportion of 97.89%, while only 2.11% Zn samples were in Safety Use II. As a whole, eight heavy metals could be ranked from more to less polluted as Hg > Cu > Cd > Pb > Zn > Cr/As/Ni.

Although most soil heavy metal samples were in Priority Protection I (Table 3), the obvious Hg and Cu pollution could not be ignored, which would affect comprehensive

pollution evaluation to a large extent (Table 4). It is obvious that great differences of soil pollution existed among eight heavy metals. Except Cr, As, and Ni, all the heavy metals had polluted samples with different proportions. Among them, the proportion of Hg polluted samples was the largest, reaching up to 24.21%. Detailly, 16.54% samples were in Slight pollution Grade, and 5.71% samples were in Mild pollution Grade, and 1.95% samples were even in Moderate pollution Grade. And the proportion of Cu polluted samples ranked the second, whose 12.48% samples were in Slight pollution Grade. In addition, Pb, Cd, and Zn polluted samples in Slight pollution Grade accounted for 4.36, 7.37, and 2.11% respectively.

From the perspective of comprehensive evaluation results, more than half of samples were not safe (Fig. 5a). Specifically speaking, 30.38% samples were in Alert Grade, which needed attention to soil heavy metal pollution. 21.05% samples were in Mild pollution Grade, indicating that heavy metal pollutants had exceeded background and soil started to be polluted. And 3.91% samples were even in Moderate pollution Grade, indicating obvious soil pollution. Spatially, most areas were not safe, and only a small part in southeast Yinzhou district and east Beilun district were in Safety Grade (Fig. 5b). Since polluted soil samples were concentratedly aggregated in middle east Jiangbei district, especially the boundary of Zhenhai and Jiangbei district,

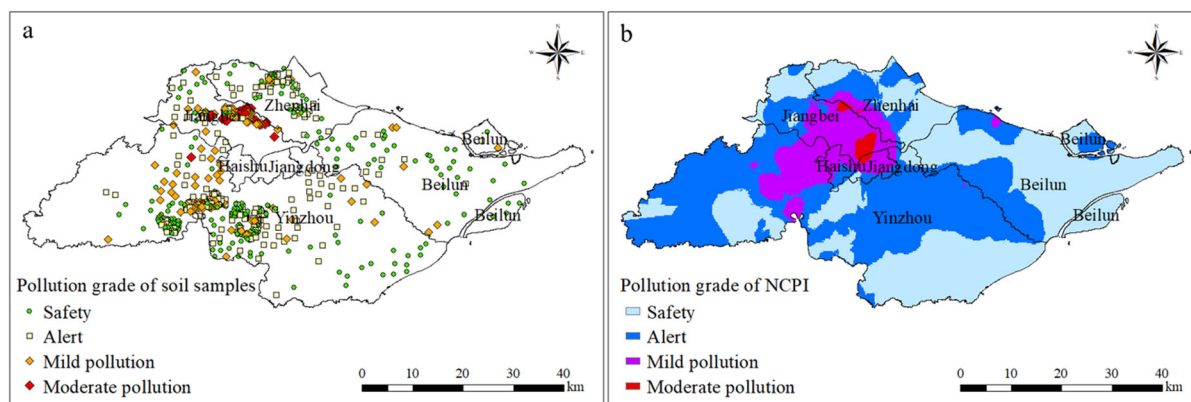


Fig. 5 Pollution grade of soil samples **a** and NCPI **b**

almost two-thirds areas of Jiangbei district were polluted. Moreover, the NCPI had obvious core areas with high values in the boundary of Jiangbei and Zhenhai district as well as in the boundary of Jiangbei and Jiangdong district. In the northwest part of study region, polluted areas were distributed with the center of Jiangbei district, and crossed five districts from northeast to southwest. As for Yinzhou district, the majority of areas were worth attention due to overwhelming soil samples of Alert Grade.

Classification of Pollution Risk Management and Control Zones

The eleven socio-environmental indicators of potential pollution impact factors presented different spatial features (Fig. 6). On the whole, the NDVIs were relatively low. The elevations and slopes had the same tendency, where the middle parts were low while high values fell on west corner and southeast part. On the contrary, roads and water bodies were concentratedly distributed in the middle-low areas. Specifically, the roadways crisscrossed all over the study area, while the railways stretched surrounding the urban center. And most of water bodies were scattered throughout the study area and the main river ran through the urban center. The population densities were undoubtedly the highest in the urban center and gradually decreased from center to edge. The north part of study region had relatively high fertilizer input, while the west part had relatively high pesticide input. Since the study region was in southeast China, precipitations were universally high especially the south and southwest parts. The spatial distribution of polluting enterprise density was similar to population density in marginal areas but opposite in central areas. And polluting enterprises were usually sited around the urban center because of convenient transportation and relatively inexpensive rents. The fertilizer input, pesticide input, and polluting

enterprise density were all relatively high close to the urban center, which were in line with NCPI spatially.

Four pollution risk management and control zones were classified based on SOM model. The classification accuracy is 94%. Finally, we obtained four characteristic zones, i.e., Monitored Zone with High-risk Pollution in central city (Zone MHP), Controlled Zone with Severe Pollution in sub-center of city (Zone CSP), Protected Zone with Ecological Conservation in marginal city (Zone PEC) and Restricted Zone with Potential Pollution in suburban city (Zone RPP) (Fig. 7).

One-way variance analysis could evaluate whether there existed good spatial variability of soil heavy metals among four zones. Evaluation results showed that all the heavy metals had extremely significant differences at the 99% confidence level (Table 5). It is obvious that SOM model performed well in classifying pollution risk management and control zones, i.e., the heterogeneity among four zones was high, while the homogeneity within each zone was high. Specifically, mean heavy metal contents in Zone CSP were generally high, and mean Cr, Hg, As, Cu, Ni contents were the highest among all zones respectively. Since Zone CSP was located in core area and vicinities of eight heavy metal high values, the spatial distributions of mean heavy metal contents were in line with that of heavy metal high-value areas (Fig. 4a, d–f, h). In Zone PEC, mean Pb, Cd, Zn contents were the highest among all zones respectively, which was consistent with the spatial distribution that one of towns in this zone was located in core areas of Pb, Cd, Zn high values. And mean Cr, As, Ni contents were the lowest among all zones respectively, which was consistent with the spatial distribution that this zone was located in Cr, As, Ni low-value areas (Fig. 4a, e, and h). Though mean heavy metal contents in Zone RPP were generally low and even the lowest, it was in line with the fact that they were basically distributed in heavy metal low-value areas (Fig. 4).

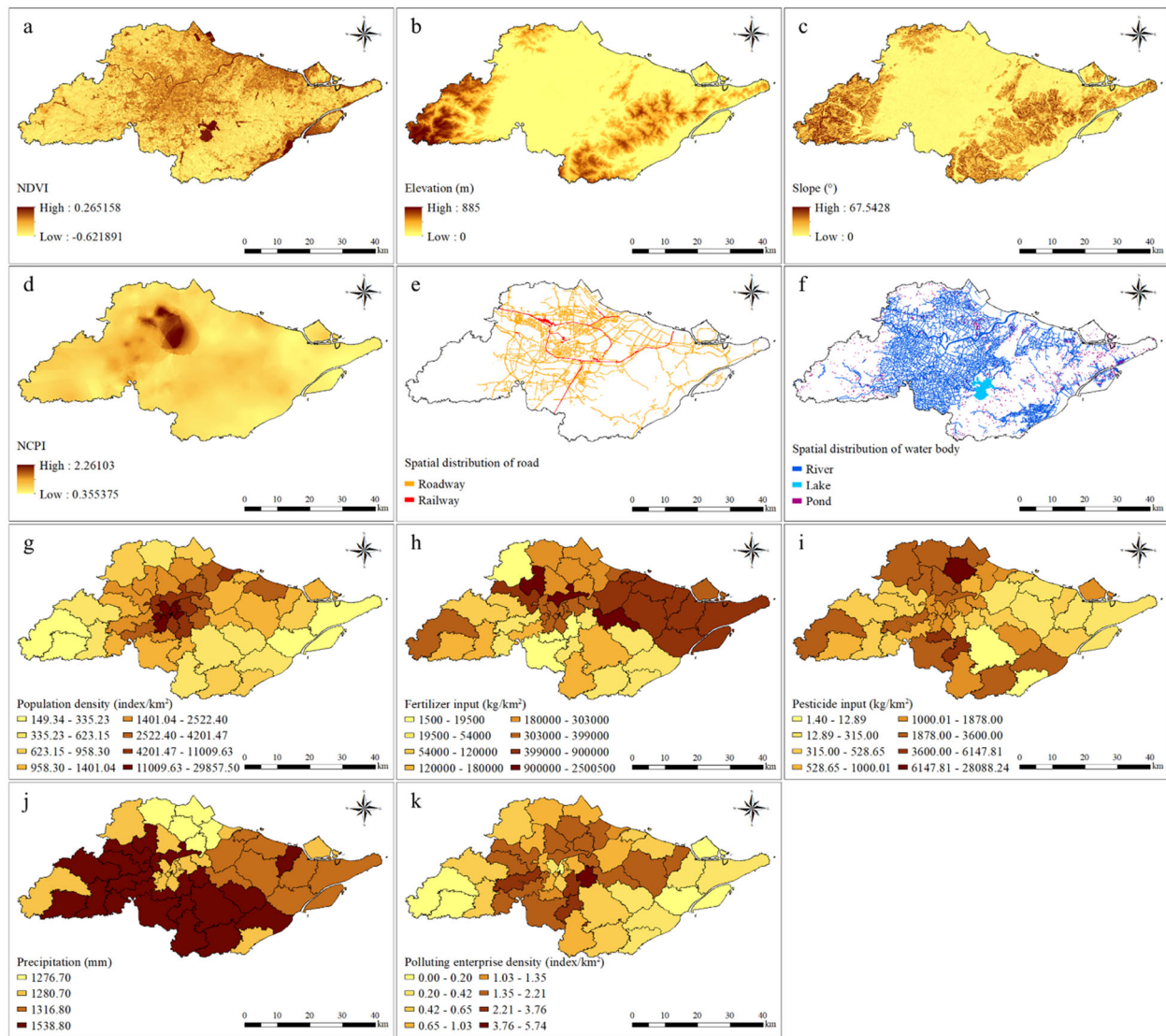


Fig. 6 The spatial distributions of eleven socio-environmental indicators

Based on good spatial variabilities, zonal statistics of socio-environmental indicators were calculated (Table 6). As a whole, NDVI was the highest in Zone PEC, and relatively high in Zone CSP and Zone RPP, but the lowest in Zone MHP. Although both elevation and precipitation were highest in Zone PEC respectively, elevation was obviously low in all other zones while precipitation was still relatively high in Zone CSP and Zone RPP. Slope was generally high among all zones. And the highest one fell on Zone PEC while slope in Zone MHP was distinctively low. NCPI was the highest in Zone MHP but obviously low in Zone RPP. Road density and water body density had similar tendencies. Both of them were highest in Zone MHP but lowest in Zone PEC. Population density was prominently high in Zone MHP but fairly low in all other zones especially Zone PEC. Analogously, both fertilizer input and

pesticide input were overall low. Fertilizer input was the highest in Zone RPP where pesticide input was the lowest. As to polluting enterprise density, the highest one was in Zone CSP.

Zone MHP contained five towns with concentrated distributions. It was located in the central part that was mainly urban land with a high population density as well as numerous roads and water bodies. Therefore, all the road density, water body density, and population density of Zone MHP were the highest, while other indicators (e.g., NDVI, elevation, and slope) were the lowest. Due to the heavy pollution caused by Pb and Hg, the NCPI of Zone MHP was distinctly the highest. As the main urban area, the heavy metal pollution is principally caused by longtime human activities of all sorts, such as incineration of domestic waste, Hg leak of electronic waste, and residue of Pb-containing

Fig. 7 Spatial distribution of pollution risk management and control zones based on SOM model

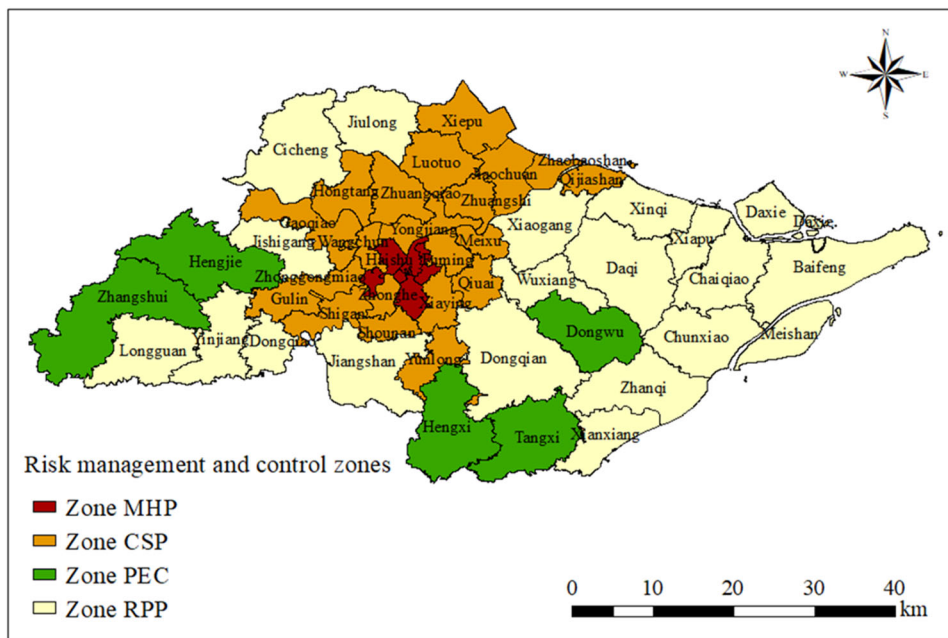


Table 5 One-way variance analysis and mean values of soil heavy metals of four zones

Zones	No. of samples	Soil heavy metals								
		pH	Cr	Pb	Cd	Hg	As	Cu	Zn	Ni
Zone MHP	0	–	–	–	–	–	–	–	–	–
Zone CSP	354	5.41	88.22	53.79	0.20	0.70	7.68	43.02	125.14	35.15
Zone PEC	25	5.15	47.52	55.11	0.25	0.36	5.26	38.46	130.19	18.82
Zone RPP	286	5.48	72.54	48.18	0.21	0.37	6.79	36.18	118.83	29.55
Variance analysis	F	1.724	105.932	16.857	6.349	78.770	33.983	30.559	4.767	80.830
	Prob > F	0.179	0.000	0.000	0.002	0.000	0.000	0.000	0.009	0.000

There was no sample in Zone MHP. The units of mean values of Cr, Pb, Cd, Hg, As, Cu, Zn, and Ni were mg/kg

gasoline (Men et al. 2018). In this zone, it is necessary to strengthen supervision as well as take prevention and control measures. For one thing, we can implement garbage classification, advocate cars with clean energy, and forbid vehicles with excessive emission (Pontau et al. 2015). For another, we can adopt biological or chemical approaches to eliminate the existing heavy metal pollution (Liu et al. 2018; Song et al. 2017).

Zone CSP had quadruple numbers of towns as Zone MHP. It was located in the central part with concentrated distributions, entirely surrounding Zone MHP. And it comprised major construction land and minor agricultural land. Similar to Zone MHP, road density and water body density were high in these towns, indicating convenient transportation in Zone CSP. It is worth noting that polluting enterprise density in Zone CSP was far ahead any other zones. Since agricultural land was one of the main land-use types, NDVI, fertilizer input, pesticide input, and precipitation were relatively high in this zone. As a

consequence, the NCPI was relatively high caused by serious Cr, Cu, Zn, and Ni pollution. As the permitted construction area that is also urban sprawl area, the heavy metal pollution principally is attributed to industrial and agricultural production, including excessive input of fertilizer and pesticide, waste water of polluting industry, waste gas of mineral exploitation and coal combustion (Yang et al. 2018). In this zone, we should conduct improvements from two aspects. From an agricultural perspective, we can actively promote organic fertilizer, strictly restrict sewage irrigation, and rationally plan agricultural land distribution. From an industrial perspective, we can inspect enterprises with probable pollution, reorganize enterprises with existent pollution and close enterprises with exorbitant pollution.

Zone PEC covering five towns distributed scatteredly on the edge of study region, which was contrary to the former two zones. Owing to the large area of forestland, it had extremely low population density, fertilizer input, pesticide input, and polluting enterprise density but dramatically high

Table 6 Mean values of socio-environmental indicators of four pollution risk management and control zones

Socio-environmental indicators	Zone MHP	Zone CSP	Zone PEC	Zone RPP
NDVI	0.284	0.502	0.648	0.482
Elevation	0.014	0.014	0.603	0.145
Slope	0.238	0.833	0.958	0.611
NCPI	0.443	0.386	0.215	0.170
Road density	0.665	0.553	0.049	0.210
Water body density	0.445	0.409	0.055	0.250
Population density	0.651	0.096	0.010	0.029
Fertilizer input	0.140	0.143	0.058	0.244
Pesticide input	0.061	0.191	0.064	0.029
Precipitation	0.015	0.542	0.803	0.409
Polluting enterprise density	0.146	0.355	0.086	0.133

The mean values of eleven socio-environmental indicators were calculated after standardization

NDVI, elevation, slope and precipitation. Although environmental indicators were high and social indicators were low, there still existed soil heavy metal pollution to some extent because of positive NCPI caused by Pb, Cd, and Zn pollution. As the prohibited construction area within the ecological red line, the heavy metal pollution may derive from historical or natural factors, such as high heavy metal in earth crust, downwind waster gas of polluting enterprise transmitted through wind and rainfall (Pan et al. 2017). In this zone, we should focus on ecological protection to dispose existing pollution and prohibit polluting activities. We can plant applicable vegetation to decontaminate heavy metals in soil. For instance, planting poplars has a great purification effect on Cd. Moreover, we can control the dust of building operations and the discharge of downwind polluting enterprises (Vareda et al. 2019).

Zone RPP covering twenty towns had large areas that were separated by Zone CSP. It was distributed across the whole study region mainly in the east, where land-use types were very complex including agricultural land, forestland, and construction land. Although the fertilizer input and contents of As and Ni in these towns were relatively high, the NCPI was unexpectedly low indicating relatively low heavy metal pollution risk. As the restricted construction area, the relatively high contents of As and Ni may be caused by the three industrial wastes of polluting enterprises. In this zone, we should lay emphasis on ecological conservation to strictly restrict the increase of polluting enterprises and intensively supervise discharge of existing enterprises (Li et al. 2019; Vareda et al. 2019).

Conclusion

In order to better classify reasonable and practical pollution risk management and control zones, we applied the self-organizing mapping (SOM) model in an industrial developed city. The results showed that heavy metal pollution was serious due to high contents of eight heavy metals (i.e., Cr, Pb, Cd, Hg, As, Cu, Zn, and Ni). Spatially, heavy metal pollution was principally concentrated in southeast Zhenhai district and the junction of Haishu, Jiangbei, Jiangdong, and Yinzhou districts. Furthermore, although more than 75% heavy metal samples had negligible risks, the notable Hg and Cu pollution could greatly affect comprehensive soil pollution, which should not be overlooked. More than 50% of the study region were polluted at varying degrees, where the center of middle east Jiangbei district was the most obvious polluted area. Our study implies that the pollution of classified four risk management and control zones, i.e., Monitored Zone with High-risk Pollution, Controlled Zone with Severe Pollution, Protected Zone with Ecological Conservation and Restricted Zone with Potential Pollution, might be attributed to human activities, industrial and agricultural production, historical or natural factors, respectively. Our study further sheds light on the prevention and control of heavy metal pollution, which can provide a solid foundation for decision-making on risk management and control of environmental pollution, as well as provide theoretical and methodological guidance for improving public governance theory, enhancing land environment quality and safeguarding human health.

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Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

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References

- Chen T, Lei M, Yang J, Zhou X (2014) Discussion on zoning of soil environmental risk control and remediation contaminated by heavy metals on regional scale. *PCAS* 29:321–326. <https://doi.org/10.3969/j.issn.1000-3045.2014.03.009>

- Cheng H, Li M, Zhao C, Li K, Peng M, Qin A, Cheng X (2014) Overview of trace metals in the urban soil of 31 metropolises in China. *J Geochem Explor* 139:31–52. <https://doi.org/10.1016/j.gexplo.2013.08.012>
- Chu H, Lin Y, Jang C, Chang T (2010) Delineating the hazard zone of multiple soil pollutants by multivariate indicator kriging and conditioned Latin hypercube sampling. *Geoderma* 158:242–251. <https://doi.org/10.1016/j.geoderma.2010.05.003>
- D'Emilio M, Caggiano R, Macchiato M, Ragosta M, Sabia S (2013) Soil heavy metal contamination in an industrial area: analysis of the data collected during a decade. *Environ Monit Assess* 185:5951–5964. <https://doi.org/10.1007/s10661-012-2997-y>
- Gao Y, Ji H (2018) Microscopic morphology and seasonal variation of health effect arising from heavy metals in PM2.5 and PM10: One-year measurement in a densely populated area of urban. *Beij Atmos Res* 212:213–226. <https://doi.org/10.1016/j.atmosres.2018.04.027>
- Huang Y, Chen Q, Deng M, Japenga J, Li T, Yang X, He Z (2018) Heavy metal pollution and health risk assessment of agricultural soils in a typical peri-urban area in southeast China. *J Environ Manag* 207:159–168. <https://doi.org/10.1016/j.jenvman.2017.10.072>
- Hu B, Jia X, Hu J, Xu D, Xia F, Li Y (2017) Assessment of heavy metal pollution and health risks in the soil-plant-human system in the Yangtze River delta, China. *Int J Environ Res Public Health* 14:1042. <https://doi.org/10.3390/ijerph14091042>
- Jia L, Yang F, Zhang S, Lin Y, Wang J (2015) Analysis on soil environmental function zoning study progress. *Chin J Agric Resour Reg Plann* 36:107–114. <https://doi.org/10.7621/cjarrp.1005-9121.20150118>
- Keshavarzi A, Kumar V (2019) Ecological risk assessment and source apportionment of heavy metal contamination in agricultural soils of Northeastern Iran. *Int J Environ Health Res* 29:544–560. <https://doi.org/10.1080/09603123.2018.1555638>
- Kim DG, Kang HM, Ko SO (2019) Reduction of non-point source contaminants associated with road-deposited sediments by sweeping. *Environ Sci Pollut Res* 26:1192–1207. <https://doi.org/10.1007/s11356-017-0192-y>
- Kohonen T (1990) The self-organizing Map. *Proc IEEE* 78:1464–1480. <https://doi.org/10.1109/5.58325>
- Kohonen T (2006) Self-organizing neural projections. *Neur Netw* 19:723–733. <https://doi.org/10.1016/j.neunet.2006.05.001>
- Kohonen T (2013) Essentials of the self-organizing map. *Neur Netw* 37:52–65. <https://doi.org/10.1016/j.neunet.2012.09.018>
- Li C, Yuan B, Zhang Y (2019) Effect assessment of ecological construction in China from 2008 to 2014. *Pol J Environ Stud* 28:1241–1246. <https://doi.org/10.15244/pjoes/85945>
- Li Y, Zhu A, Shi Z, Liu J, Du F (2016) Supplemental sampling for digital soil mapping based on prediction uncertainty from both the feature domain and the spatial domain. *Geoderma* 284:73–84. <https://doi.org/10.1016/j.geoderma.2016.08.013>
- Li Z, Su H, Wang L, Hu D, Zhang L, Fang J, Jin M, Fiati K, Samuel S, Song X, Shi H, Zhao J, Mao G (2018) Epidemiological study on metal pollution of Ningbo in China. *Int J Environ Res Public Health* 15:424. <https://doi.org/10.3390/ijerph15030424>
- Liang J, Feng C, Zeng G, Gao X, Zhong M, Li X, Li X, He X, Fang Y (2017) Spatial distribution and source identification of heavy metals in surface soils in a typical coal mine city, Lianyuan, China. *Environ Pollut* 225:681–690. <https://doi.org/10.1016/j.envpol.2017.03.057>
- Liu L, Li W, Song W, Guo M (2018) Remediation techniques for heavy metal-contaminated soils: principles and applicability. *Sci Total Environ* 633:206–219. <https://doi.org/10.1016/j.scitotenv.2018.03.161>
- Liu R, Borthwick A (2011) Measurement and assessment of carrying capacity of the environment in Ningbo, China. *J Environ Manag* 92:2047–2053. <https://doi.org/10.1016/j.jenvman.2011.03.033>
- Liu Y, Feng Y, Zhao Z, Zhang Q, Su S (2016) Socioeconomic drivers of forest loss and fragmentation: a comparison between different land use planning schemes and policy implications. *Land Use Policy* 54:58–68. <https://doi.org/10.1016/j.landusepol.2016.01.016>
- Lü J, Jiao W, Qiu H, Chen B, Huang X, Kang B (2018) Origin and spatial distribution of heavy metals and carcinogenic risk assessment in mining areas at You'xi County southeast China. *Geoderma* 310:99–106. <https://doi.org/10.1016/j.geoderma.2017.09.016>
- Marrugo-Negrete J, Pinedo-Hernández J, Díez S (2017) Assessment of heavy metal pollution, spatial distribution and origin in agricultural soils along the Sinu River Basin, Colombia. *Environ Res* 154:380–388. <https://doi.org/10.1016/j.envres.2017.01.021>
- Men C, Liu R, Xu F, Wang Q, Guo L, Shen Z (2018) Pollution characteristics, risk assessment, and source apportionment of heavy metals in road dust in Beijing, China. *Sci Total Environ* 612:138–147. <https://doi.org/10.1016/j.scitotenv.2017.08.123>
- Ministry of Ecology and Environmental of the People's Republic of China (2018) Soil environmental quality risk control standard for soil contamination of agricultural land. GB 15618-2018, Beijing
- Mu T, Wu T, Zhou T, Li Z, Ouyang Y, Jiang J, Zhu D, Hou J, Wang Z, Luo Y, Christie P, Wu L (2019) Geographical variation in arsenic, cadmium, and lead of soils and rice in the major rice producing regions of China. *Sci Total Environ* 677:373–381. <https://doi.org/10.1016/j.scitotenv.2019.04.337>
- National Environmental Monitoring Center of the People's Republic of China (1990) The background concentrations of soil elements of China. China Environmental Science Press, Beijing
- NSPCIR (2014) The National Soil Pollution Condition Investigation Report. Ministry of Environmental Protection and Ministry of Land and Resources of the People's Republic of China. Accessed 17th, April 2014
- Pan H, Lu X, Lei K (2017) A comprehensive analysis of heavy metals in urban road dust of Xi'an, China: Contamination, source apportionment and spatial distribution. *Sci Total Environ* 609:1361–1369. <https://doi.org/10.1016/j.scitotenv.2017.08.004>
- Pan L, Ma J, Hu Y, Su B, Fang G, Wang Y, Wang Z, Wang L, Xiang B (2016) Assessments of levels, potential ecological risk, and human health risk of heavy metals in the soils from a typical county in Shanxi Province, China. *Environ Sci Pollut Res* 23:19330–19340. <https://doi.org/10.1007/s11356-016-7044-z>
- Pontau P, Hou Y, Cai H, Zhen Y, Jia X, Chiu ASF, Xu M (2015) Assessing land-use impacts by clean vehicle systems. *Resour Conserv Recycl* 95:112–119. <https://doi.org/10.1016/j.resconrec.2014.12.008>
- Song B, Zeng G, Gong J, Liang J, Xu P, Liu Z, Zhang Y, Zhang C, Cheng M, Liu Y, Ye S, Yi H, Ren X (2017) Evaluation methods for assessing effectiveness of in situ remediation of soil and sediment contaminated with organic pollutants and heavy metals. *Environ Int* 105:43–55. <https://doi.org/10.1016/j.envint.2017.05.001>
- State Council of the People's Republic of China (2013) Arrangement of soil environmental protection and comprehensive management. State Council of the People's Republic of China, Beijing
- State Council of the People's Republic of China (2016) Action plan for the prevention and control of soil pollution. State Council of the People's Republic of China, Beijing
- Sun M, Wang T, Xu X, Zhang L, Li J, Shi Y (2020) Ecological risk assessment of soil cadmium in China's coastal economic development zone: a meta-analysis. *Eco Health Sustain* 6. <https://doi.org/10.1080/20964129.2020.1733921>

- Vareda JP, Valente AJM, Duraes L (2019) Assessment of heavy metal pollution from anthropogenic activities and remediation strategies: A review. *J Environ Manag* 246:101–118. <https://doi.org/10.1016/j.jenvman.2019.05.126>
- Wang B, Li H, Sun D (2014) Social-ecological patterns of soil heavy metals based on a self-organizing map (SOM): a case study in Beijing, China. *Int J Environ Res Public Health* 11:3618–3638. <https://doi.org/10.3390/ijerph110403618>
- Wang M, Liang L, Siu W, Fan D, Sun H, Zhao H, Zhou G, Wu W (2019) Loss accounting of environmental pollution within Pearl River Delta region, South China. *Environ Pollut* 249:676–685. <https://doi.org/10.1016/j.envpol.2019.03.081>
- Wei H, Luo M, Ju Z, Wu K (2018) Risk zoning and governance of heavy metal pollution in agricultural land. *Chin J Agric Resour Reg Plann* 39:82–87. <https://doi.org/10.7621/cjarrp.1005-9121.20180212>
- Yang Q, Li Z, Lu X, Duan Q, Huang L, Bi J (2018) A review of soil heavy metal pollution from industrial and agricultural regions in China: Pollution and risk assessment. *Sci Total Environ* 642:690–700. <https://doi.org/10.1016/j.scitotenv.2018.06.068>
- You H (2017) Agricultural landscape dynamics in response to economic transition: Comparisons between different spatial planning zones in Ningbo region, China. *Land Use Policy* 61:316–328. <https://doi.org/10.1016/j.landusepol.2016.11.025>
- Yu B, Wu K (2018) Eco-risk regionalization and control of heavy metal in soil with high background value. *Acta Agric Univ Jiangx* 40:629–634. <https://doi.org/10.13836/j.jjau.2018081>
- Zang F, Wang S, Nan Z, Ma J, Zhang Q, Chen Y, Li Y (2017) Accumulation, spatio-temporal distribution, and risk assessment of heavy metals in the soil-corn system around a polymetallic mining area from the Loess Plateau, northwest China. *Geoderma* 305:188–196. <https://doi.org/10.1016/j.geoderma.2017.06.008>
- Zeng X, Xu J, Huang Q, Tang S, Li Y, Li F, Zhou D, Wu Z (2015) Some deliberations on the issues of heavy metals in farmlands of China. *Acta Ped Sin* 50:186–194
- Zhang H, Wang Z, Zhang Y, Hu Z (2012) The effects of the Qinghai-Tibet railway on heavy metals enrichment in soils. *Sci Total Environ* 439:240–248. <https://doi.org/10.1016/j.scitotenv.2012.09.027>
- Zhang P, Qin C, Hong X, Kang G, Qin M, Yang D, Pang B, Li Y, He J, Dick RP (2018) Risk assessment and source analysis of soil heavy metal pollution from lower reaches of Yellow River irrigation in China. *Sci Total Environ* 633:1136–1147. <https://doi.org/10.1016/j.scitotenv.2018.03.228>
- Zheng X, Lu A, Gao X, Zhao J, Zheng D (2002) Contamination of heavy metals in soil present situation and method. *Soil Environ Sci* 11:79–84. <https://doi.org/10.16258/j.cnki.1674-5906.2002.01.020>