Stochastic Environmental Research and Risk Assessment
https://doi.org/10.1007/s00477-020-01806-z

ORIGINAL PAPER

Influence factor analysis of soil heavy metal Cd based on the GeoDetector

Yunting Jiang[1] · Yingjun Sun[1] · Liping Zhang[1] · Xvlu Wang[1]

Abstract
As a variant with high spatial differentiation and continuous space time, soil is polluted by various artificial or natural factors, and the pollution of heavy metal Cd is one of the more serious problems. This study took Liaocheng, as the research area and sampled the points in a grid center of 10 km × 10 km to obtain the sampling data of heavy metal Cd in the soil surface layer at depths of 0–20 cm. We selected the environmental background value of Shandong Province as the standard and used the geological accumulation index method to evaluate the pollution status of heavy metal Cd in the experimental area, concluding that there was a moderate level of Cd pollution in the study area. On this basis, we selected soil pH value, soil sub-class, annual average precipitation, annual average surface temperature, elevation data, and change in GDP as the six major influencing factors of heavy metal Cd in the study area by GeoDetector analysis. The correlation between soil heavy metal Cd and the impact factors was explored. The results revealed that soil pH and elevation exerted a large influence on soil Cd content, while annual average surface temperature had the least influence. The interaction of various influencing factors on heavy metal Cd was nonlinearly enhanced, especially the elevation data and annual average precipitation data.

Keywords Soil heavy metal Cd · Heavy metal pollution assessment · Influence factors of heavy metal · GeoDetector

1 Introduction

Given the unreasonable pollution levels resulting from both human and natural factors, the problem of soil environmental pollution in China is becoming more and more serious, and soil quality faces major challenges. Cheng (2003) pointed out that the geological background value of heavy metals in China is relatively low. Some studies have shown that soil, water, air, and plants have been seriously polluted by heavy metals, and in recent decades, direct photographs have been taken revealing human activities. Heavy metals making their way into the food chain are affecting human health (Cheng 2003). With the rapid development of society and the economy around the globe, soil pollution is not only one of the serious problems in China but also exists in all parts of the world (Yang et al. 2018). Ways of effectively dealing with soil pollution problems, tracing their origins, and exploring the factors affecting the distribution characteristics of heavy metal ions in soil are all key. Therefore, in the past decade, a great deal of research and analysis on the driving factors affecting soil heavy metal pollution have been carried out both in China and abroad.

The most commonly used techniques for studying soil heavy metal content and impact factors are geostatistical methods, spatial regression analysis, and multivariate statistical analysis. Liu et al. used the geographically weighted regression model to compare the relationship between the contents of the heavy metals Pb and Cd and the influencing factors in the soil, concluding that soil pH, organic matter, and nitrogen and phosphorus content are important factors affecting the soil Pb and Cd content (Liu et al. 2013a, b). Dai et al. used multi-statistical methods such as principal component analysis, correlation analysis, and geostatistical methods to detect the source and spatial distribution of nine

✉ Yunting Jiang
329559416@qq.com

✉ Yingjun Sun
sdjzusyj@126.com

[1] College of Surveying and Mapping Geo-Informatics, Shandong Jianzhu University, Jinan, Shandong, China

Published online: 30 April 2020

heavy metals—As, Cd, Co, Cr, Cu, Hg, Ni, Pb, and Zn (Dai et al. 2015); Lv et al. employed the kriging interpolation method and multiple regression analysis to study the dependence of heavy metals on different spatial scales, and determined the spatial multi-scale under the influence factor (Lv et al. 2013).

When investigating soil heavy metal influence factors, most researchers have analyzed the impact of single factors and did not consider the impact intensity of multiple factor interaction. In 2010, Wang et al. used spatial differentiation to develop geographical detector software. Geographical detector software can reveal the influence of a single factor on a dependent variable, as well as the influence of two-factor interaction (Wang and Xu 2017). Li et al. simulated the spatial distribution of the heavy metals Pb, Cd, As, Cr, and Hg in five soils by spatial interpolation, and utilized a geographical detector to determine the correlation and interaction between six influencing factors and soil heavy metal content (Li et al. 2017). Chen et al. used geographical detector and random forest models to analyze the driving factors affecting the spatial distribution of soil heavy metals (Chen et al. 2019); Zhang et al. employed geostatistical methods and geographical detector models to reveal soil heavy metal pollution and the factors driving it. The relationship between the influencing factors was discussed, and the source analysis of soil heavy metals was carried out in combination with the Unmix 6.0 model (Zhang et al. 2019). Ren et al. used a geographical detector model to detect the sources of heavy metal pollutants in agricultural soils (Ren et al. 2019).

The "National Soil Pollution Status Survey Bulletin" of April 17, 2014 revealed that the over-standard rate of heavy metals and other pollutants in cultivated soil in China had reached 19.4%, and the pollution situation was not optimistic. There were significant differences in the heavy metals of farmland soils for different research scales, and the probability of Cd elements in farmland soils was the highest (Xu et al. 2018). Soil heavy metal Cd is more easily absorbed by plants, such as wheat and rice, and is the main source of cadmium transport into the human food chain (Chaney et al. 2016; Dong et al. 2001).

In Liaocheng, the primary grain-producing area of Luxi, the main grain varieties are wheat and corn, and Cd has different effects on their crop yields and crop quality. Previous research on the heavy metal pollution in Liaocheng soil has only considered its content and distribution, with few analyses on its impact factors (Liu et al. 2010, 2013a, b; Luo et al. 2017; Fu et al. 2009). This study took the Cd content in the soil sampling points of Liaocheng City, Shandong Province as the research object, then utilized ArcGIS and the geographical detector model to quantitatively and qualitatively assess the effects of Cd driving factors to explore the correlation and interaction between soil heavy metals and influencing factors (Du et al. 2016).

2 Materials and methods

2.1 Study sites

Located in the western part of Shandong Province, Liaocheng is situated on the Luxi Plain, adjacent to Henan and Hebei. It is positioned at the junction of East China, Central China, and North China. The city covers the area from 35° 05′–37° 47′ N latitude and 116°–116° 16′ E longitude, corresponding to a north–south distance of 138 km and an east–west distance of 114 km, encompassing a total area of 8715 km^2. Liaocheng is located on the impact plain of the Yellow River. The terrain is high in the southwest and low in the northeast. The average slope is approximately 1/7500 and the altitude ranges from 27.5 to 49.0 m. Liaocheng experiences a temperate continental monsoon climate. The total population is 6.39 million (as of the end of 2017) and the gross domestic product (GDP) is 315.22 billion yuan (as of 2018).

The research area includes Liaocheng County, Guan County, Shen County, Yanggu County, Dong'e County, Gaotang County, Chiping County, Dongchangfu District, the Economic and Technological Development Zone, and the municipality of Linqing City, which is under the jurisdiction of the province. Thus, a total of 9 counties, districts, and cities were in the study area.

2.2 Distribution and interactive detection

In order to obtain soil samples from the study area, GPS positioning was used to carry out point sampling in the Liaocheng area in early 2013, based on the 10 km × 10 km grid center method, and the soil surface layer from 0 to 20 cm was mixed to acquire samples. The samples were taken back to the laboratory for air drying, and the Cd concentration was determined with an atomic absorption spectrophotometer and a flameless graphite furnace device (Forstner et al. 1990; Michaela et al. 2019). This study analyzed both natural and socioeconomic factors in order to explore the driving factors that affect the distribution of heavy metals in soil. The index of each factor is shown in Table 1.

The distribution map of the soil heavy metal sampling points in the study area is shown in Fig. 1.

Soil pH value affects both migration and conversion of heavy metals (Yin et al. 2014). The pH value of the soil at each of the sampling points was measured using the potential method.

Table 1 Impact factor

Classification	Factor
Natural factor	Soil sub-category
	Soil pH
	Annual mean surface temperature
	Elevation
	Annual average precipitation
Socioeconomic factor	Change in GDP

At the 2019 National Farmland Soil Pollution Control and Technical Exchange Conference on Ecological Restoration and Industrial Poverty Alleviation in the Yangtze River Economic Belt, Zhou (2019) proposed that temperature rise throughout the day will cause soil pH to decrease and increase the effective Cd in the soil. The annual average surface temperature data were provided by the Geospatial Data Cloud site of the Computer Network Information Center, Chinese Academy of Sciences, MODLT1M China 1 km surface temperature monthly synthesis product. This contains a total of 10 years' worth of surface temperatures and nighttime surface temperatures from 2003 to 2012. These data were downscaled using conversion projection and re-sampling in order to obtain the annual average surface temperatures.

Generally speaking, the greater the elevation value, the greater the heavy metal content in the soil from the atmosphere (Ding et al. 2017). The DEM data were provided by the Geospatial Data Cloud site of the Computer Network Information Center, Chinese Academy of Sciences, SRTM 90 m resolution digital elevation product.

With the increase of rainfall, the total amount of heavy metals in soil samples has increased significantly (Yang et al. 2011). The annual average precipitation data came from the Resource Environment Data Cloud Platform of the Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences, and the annual interpolated spatial dataset 1 km for the decade 2003–2012. The annual precipitation was extracted from the soil heavy metal sampling points, and the average annual precipitation over the 10-year study period was obtained.

The development of intensive agricultural production and industrialization and the rapid expansion of cities have caused a large number of harmful substances to enter the soil, causing the soil to be enriched with heavy metal ions (Xu et al. 2010). The GDP value can indirectly reflect the development of the above factors. The GDP data comes from Liaocheng Statistical Yearbooks (2003–2012). It is the total GDP data of each county and city. The GDP data not only reflects the impact of economic development on soil heavy metal pollution, but also reflects the influence of human activities. This investigation fit the total amount of nighttime light intensity in Liaocheng with its total GDP for each year in the study period. The result that $R^2 = 0.75$ demonstrates that there is a certain positive correlation between nighttime light intensity and total GDP, thus indicating that nighttime light intensity can represent GDP to some extent. So we use the night light data as a constraint value to interpolate the GDP data. The intensity of the light in the night light data, the GDP data is interpolated

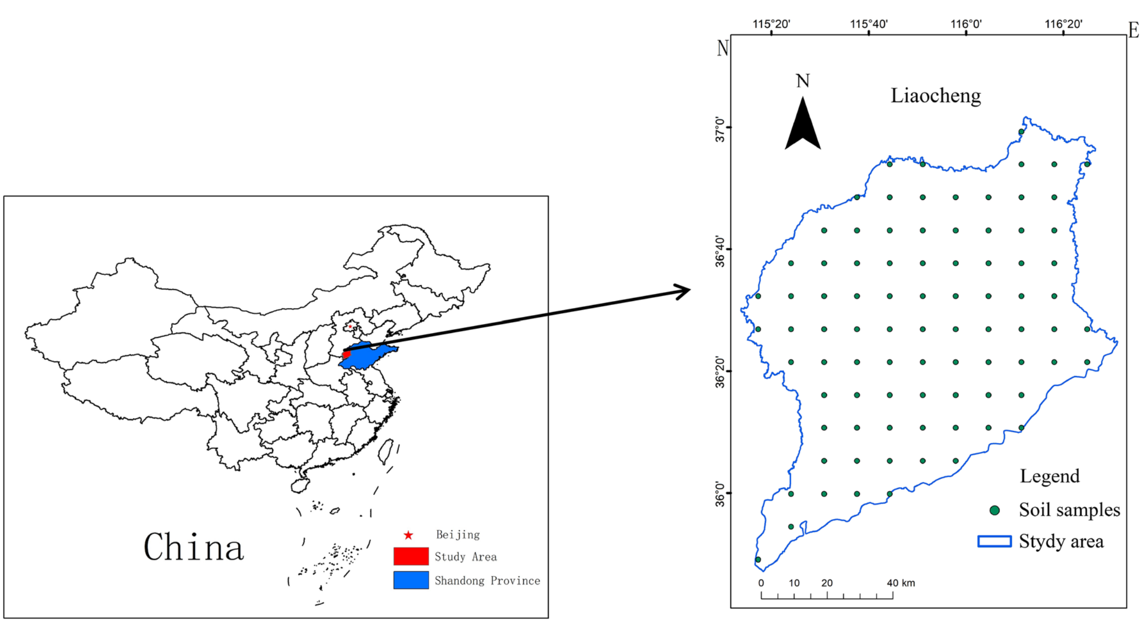


Fig. 1 Map of soil sample points in the study area

to obtain the GDP spatial distribution data of the 10 km grid.

In the past, scholars mostly chose one year of data when selecting impact factors. This article obtains the average value of all factors during the research period and uses the average value as the driving factor for later analysis. Heavy metal pollution in soil is an increasingly accumulating process, not an overnight. The average value is more able to reflect the impact on it.

2.3 Geo-accumulation index method

The geological accumulation index (CEMS 1990), also known as the Muller index, originated in Europe in the late 1960s. This method is widely used to evaluate the degree of contamination of heavy metals in sediments and their related materials. The geological accumulation index method not only evaluates the heavy metal pollution in the natural state, but also considers the heavy metal pollution caused by human activities. The formula for the geological accumulation index is as follows:

$$R_i = \log_2\left(\frac{Z_i}{1.5 * Z_{0i}}\right),$$

where R_i is the geological accumulation index of the ith pollutant; Z_i is the measured value of the ith pollutant, in mg/kg; Z_{0i} is the background value of the ith pollutant, in mg/kg; and 1.5 is the correction factor used to characterize sedimentary characteristics, rock geology, and other effects.

2.4 Geographical detector

Impact factors have a significant impact on the spatial variation of the distribution of soil heavy metals. Geographic information technology (GIS) provides an operable platform for carrying spatial information, while quantitative spatial analysis provides an understanding of the influence of each factor A powerful auxiliary tool (Wang et al. 2010). The geographical detector (GeoDetector) is a statistical method based on spatial stratification heterogeneity proposed by Jinfeng Wang from the Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences (Wang et al. 2016, 2017). The GeoDetector consists of 4 detectors, each associated with their own detection method: the Risk detector, Factor detector, Ecological detector, and Interaction detector. The Factor detector and the Interaction detector were used in this study. They can quantitatively detect the degree of influence of the independent variable on the dependent variable.

Factor detector: The influence of a driving factor X on the dependent variable Y is quantified by the q value, and the degree of spatial differentiation of Y is described by the extent that a certain driving factor X is detected. The formula for calculating q is as follows:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} = 1 - \frac{SSW}{SST},$$

$$SSW = \sum_{h=1}^{L} N_h \sigma_h^2,$$

$$SST = N\sigma^2,$$

where h = 1 to L is the stratum of the variable Y or factor X and the classification partition, as well as the number of cells in the layer h and the entire region, respectively, and also the variable Y in the layer h and the entire region, respectively The variances SSW and SST respectively represent the sum of squares and the total sum of squares; the value of q is [0,1], and the larger its value, the more obvious the differentiation of the Y space.

Interaction detector: This is detected whether the two driving factors X1 and X2 work together to increase or decrease the explanatory power of the dependent variable Y, or the influence of these factors on Y is independent. The q values of factors X1 and X2 are labeled q(X1) and q(X2) in the geographical detector, and the q(X1∩X2) values are calculated by the interaction detector when they interact. The interaction results are obtained by comparing the sizes of q(X1), q(X2), and q(X1∩X2). The interaction results of the two-factor interactions are shown in Table 2 (http://www.geodetector.cn/).

3 Results and discussion

3.1 Statistical analysis

The statistical analysis of the soil heavy metal sampling points was carried out using Pearson software, and the Cd content parameters of the soil heavy metals in Liaocheng were comprehensively analyzed by referring to the "China Soil Environment Background Value" (Hui 2017). The results are listed in Table 3.

In this experiment, the background value of 0.084 mg/kg for Shandong Province was selected as the background value of the pollutants in the geological accumulation index method. The geological accumulation index is divided into 7 grades, numerically designated 0–6, which represent pollution levels ranging from no pollution to extremely heavy pollution. The pollution assessment and results are listed in Table 4. According to the statistical analysis, 19.2% of Liaocheng has level 0 heavy metal Cd pollution, i.e., no pollution; 79.5% experiences level 1, i.e., no pollution to moderate pollution, 1.25% has level 2, i.e., moderate pollution, and 0.09% has level 3, i.e., heavy pollution.

Table 2 Results of the interactions between 2 factors

Results of interaction	Description
Weaken, nonlinear	q(X1∩X2) < Min(q(X1),q(X2))
Weaken, uni-	Min(q(X1),q(X2) < q(X∩X2) < Max(q(X1),(X2))
Enhance, bi-	q(X1∩X2) > Max(q(X1),q(X2))
Independent	q(X1∩X2) = q(X1) + q(X2)
Enhance, nonlinear	q(X1∩X2) > q(X1) + q(X2)

Table 3 Statistics for Cd characteristic content parameters of the soil heavy metals in Liaocheng

Soil heavy mental content	Shandong background value	China background value	World soil median	Minimum value	Maximum value	Average value	Standard deviation statistics
Cd (mg/kg)	0.084	0.097	0.350	0.070	0.580	0.150	0.035

Table 4 Muller index pollution assessment and results

Judgment range	Level	Degree of pollution	Contaminant geological accumulation index accounted for (%)
R < 0	0	No pollution	19.2
0 ≤ R < 1	1	No pollution to moderate pollution	79.5
1 ≤ R < 2	2	Moderate pollution	1.25
2 ≤ R < 3	3	Moderate pollution to heavy pollution	0.09

Kriging interpolation, as an unbiased optimal interpolation method based on spatial autocorrelation, is widely used to analyze the spatial distribution characteristics of soil heavy metals (Li and Shao 2019). In this study, ordinary kriging was employed to analyze the content of soil heavy metal Cd at the sampling points, thereby producing the spatial distribution map of soil heavy metal Cd content shown in Fig. 2.

According to the distribution map, the pollution level in Shenxian County was slightly more serious than that of the other counties and cities (Fig. 3). Data inquiry and site investigations revealed that there are a large number of vegetable farms in Shenxian County. Thus, the use of pesticides and fertilizers may lead to an increase in soil heavy metal Cd (Makino et al. 2016).

3.2 Analysis of factors affecting soil heavy metals

The geographical detector software is known as GeoDetector. For the independent variable X, this variable can either be a type quantity or a numerical quantity. If it is a numerical quantity, it needs to be discretized in advance. In this experiment, the parent soil subcategories were type quantities, which were numbered according to soil type, and divided into eight categories; meanwhile, the other

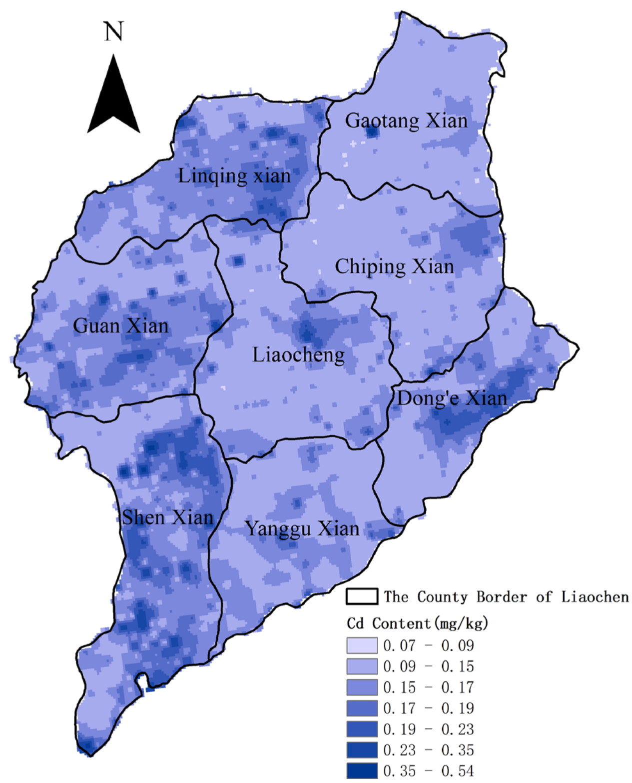


Fig. 2 Spatial distribution of heavy metal Cd content

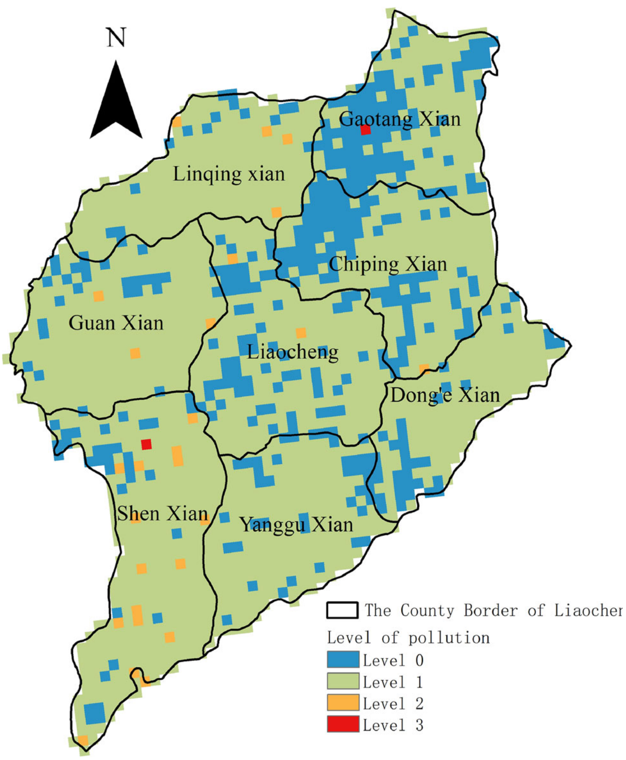


Fig. 3 Spatial distribution of the pollution index of heavy metal Cd

factors were classified according to the k-means classification method and the natural breakpoint method by comparing their respective q values. Ultimately, the classification of each factor was obtained. The soil pH and annual mean surface temperature were divided into seven categories using the natural breakpoint method. DEM, precipitation and change in GDP were classified into seven categories through k-means classification. The distributions of the various influence factors are illustrated in Fig. 4.

3.2.1 Factor detector

The effect of different factors on the Cd content in soil was detected by the GeoDetector Factor detector. The results revealed that soil pH (0.070) > elevation (0.044) > soil subcategory (0.026) > change in GDP (0.020) > annual average precipitation (0.019) > annual average surface temperature (0.012). Among these, soil pH value exhibited the strongest explanatory power for Cd content, followed by elevation, while the average annual variation of nighttime light intensity was the weakest. The detailed results are listed in Fig. 5. Different soil pH has different effects on the state exchange and migration of soil Cd, and exerts a large influence on heavy metal Cd (Webster and Oliver 2001).

3.2.2 Interaction detector

In general, external environmental conditions are complex and diverse. Therefore, it is difficult to determine the influences on the distribution of heavy metals in soil from a single factor. In this study, the interactions of the GeoDetector detectors were used to determine the distribution of heavy metals in soil under the influence of two factors. The detailed results are listed in Table 5.

It can be seen from these results that the two-factor interaction results are greater than the sum of the two-factor q values, all of which are nonlinear enhancements, where in q for (annual average precipitation∩elevation) is the largest, indicating that the joint action of annual average precipitation and elevation has the greatest influence on soil heavy metal Cd, followed by the interaction of elevation and soil pH. Except for change in GDP∩Elevation, the interaction results of other factors are non-linear enhancements.

3.2.3 Pearson correlation analysis and GeoDetector results comparison

For the correlation analysis of the direction and extent of the trend between 2 variables, three correlation coefficients are usually employed: the Pearson, Spearman, and Kendall (Zhang et al. 2015).

The Pearson correlation coefficient is a common method for measuring whether two variables have a linear relationship. The calculation formula is as follows:

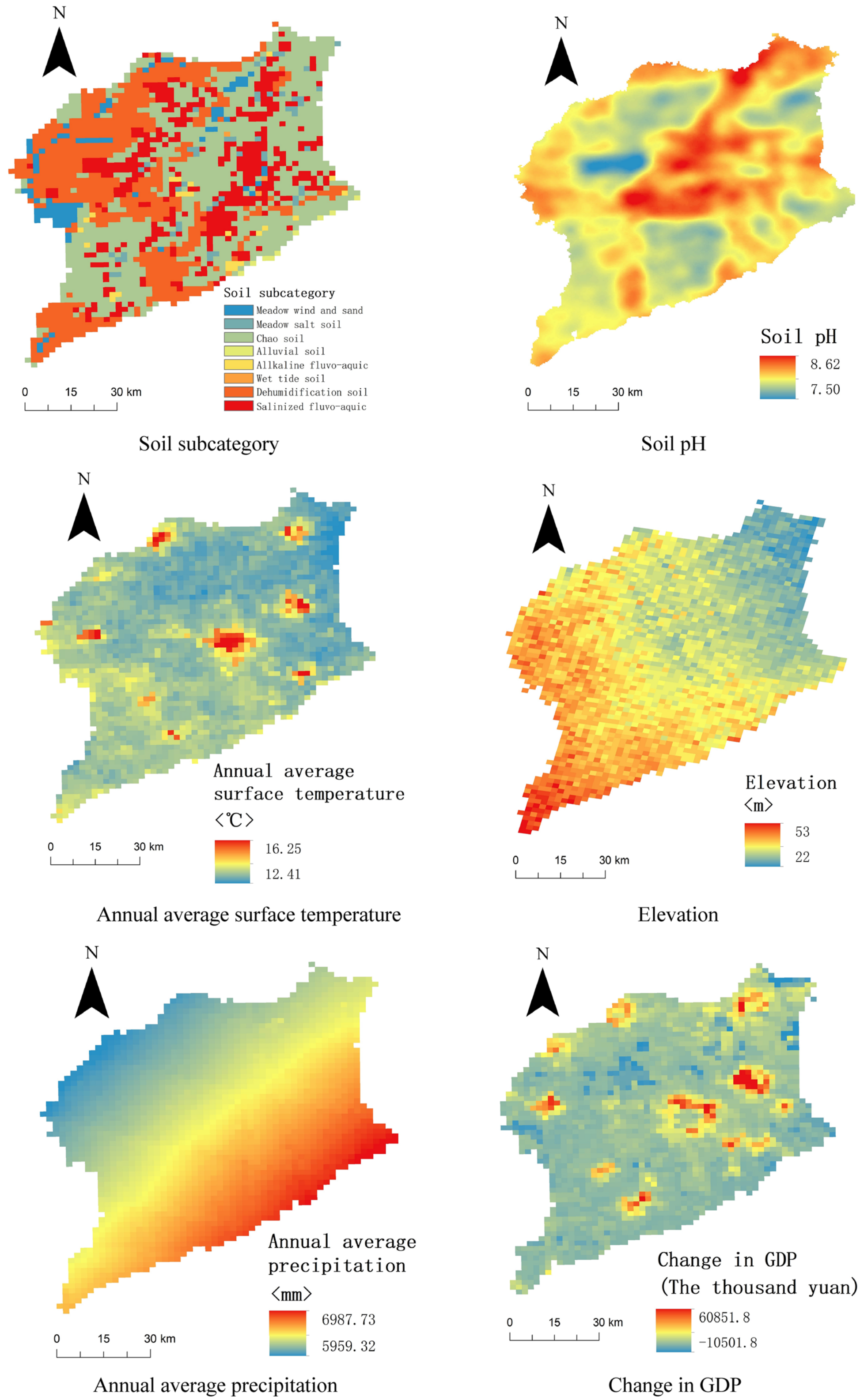
$$\mathrm{r} = \frac{N\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{N\sum x_i^2 - \left(\sum x_i\right)^2}\sqrt{N\sum y_i^2 - \left(\sum y_i\right)^2}}.$$

The Spearman and Kendall are rank correlation coefficients, and the variables calculated by the Kendall correlation coefficient are categorical variables.

In this study, the soil sub-classes were analyzed using the Kendall correlation coefficient in Pearson software correlation analysis. The other five factors were analyzed with the Pearson correlation coefficient and compared with the GeoDetector results. The comparison results are presented in Fig. 5.

It can be seen from Fig. 6 that the Pearson correlation analysis results and the geographic detector results for soil pH exerted the greatest influence on Cd, followed by elevation, although Pearson's correlation analysis indicated that the soil pH was negatively correlated with Cd. The remaining four factors were analyzed by two different methods and exhibited different changes in the influence intensity. In addition to soil pH, Pearson's correlation analysis revealed that annual average precipitation was negatively correlated with Cd.

Fig. 4 Spatial distributions of the influence factors



Pearson's correlation analysis only reflects whether there is a linear relationship between the two factors. For two factors with a non-linear relationship, even if the two parties have a strong correlation, the Pearson correlation analysis cannot determine the causality, and the value of the Pearson correlation coefficient may be close at 0. The

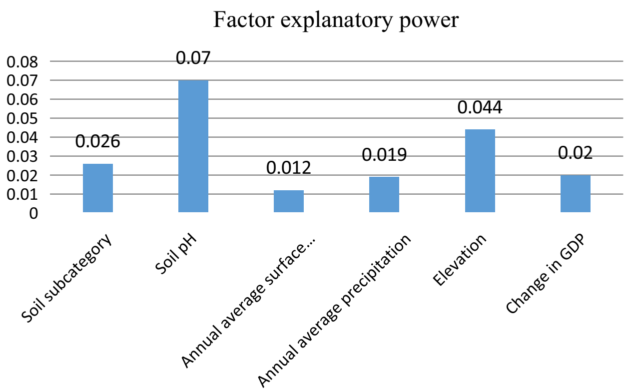


Fig. 5 Factor explanatory power

GeoDetector, however, not only can identify whether two factors are linearly related but also can identify whether there is a nonlinear relationship between them. By calculating the single-factor q value and the q value for two-factor interaction, the explanatory power of the independent variable X to the dependent variable Y is revealed. Furthermore, the spatial probe explores the heterogeneity of spatial stratification. Assuming that the independent variable X has a strong explanatory force on the dependent variable Y, then the geographical stratification of the dependent variable Y will be consistent with the stratification of the independent variable X and this. It is also the

Table 5 Interactions of different influence factors on the soil heavy metal element Cd

	Soil subcategory	Soil pH	Annual average surface temperature	Elevation	Annual average precipitation	Change in GDP
Soil subcategory	0.026					
Soil pH	0.102[a]	0.070				
Annual average surface temperature	0.060	0.093	0.012			
Elevation	0.091	0.117[a]	0.068	0.044		
Annual average precipitation	0.069	0.103[a]	0.108[a]	0.127[a]	0.019	
Change in GDP	0.054	0.090	0.047	0.057	0.073	0.020

[a]Represents the result of greater interaction

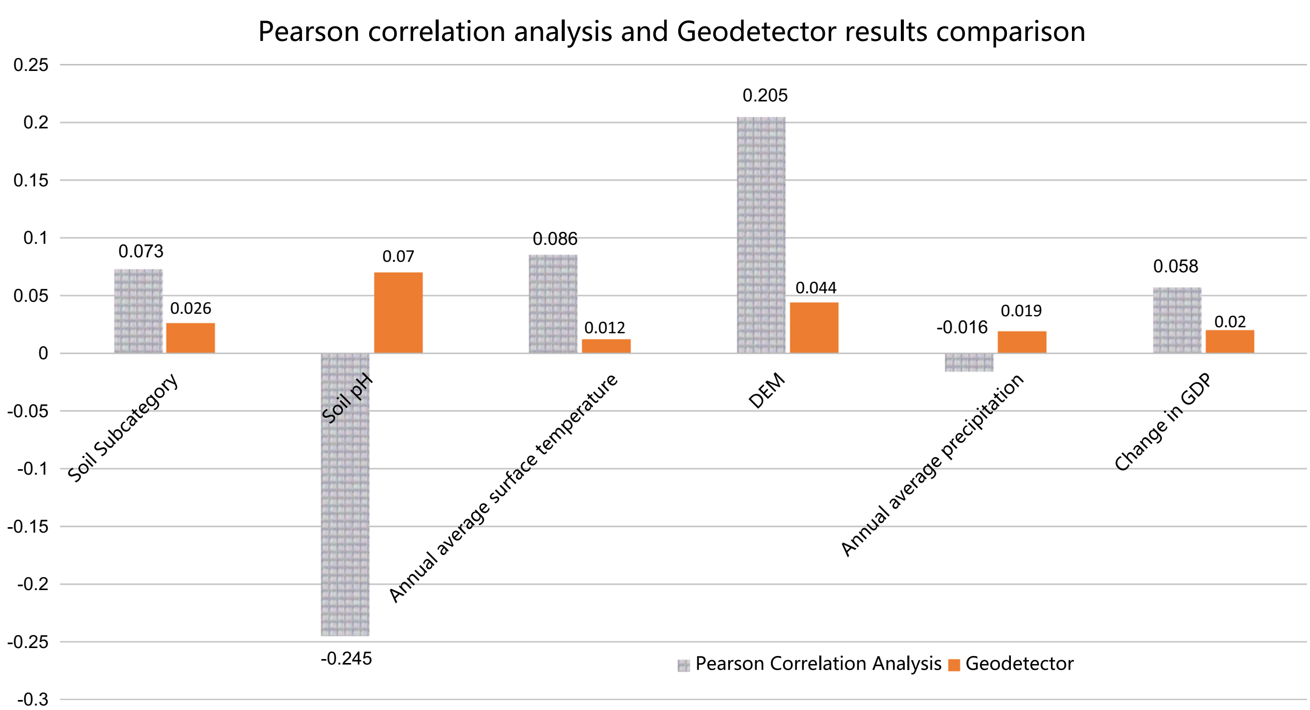


Fig. 6 Comparison of correlations between Cd and influence factors from Pearson analysis and the GeoDetector

purpose of finding the best X classification before putting the data into the GeoDetector.

4 Conclusions

(1) The results of the GeoDetector analysis showed that the PD values were small, indicating that each factor has a certain impact on the spatial distribution of soil heavy metal Cd content, but their individual impact capacity is limited. The pH value is the greatest effect. In the existing research, most of the pollution sources of soil heavy metal Cd were attributed to agricultural activities such as fertilization. In this experiment, data on fertilization were not reflected. The counties and cities in Liaocheng not only have abundant grain, fruit and vegetable production, developed paper, printing, dyeing, and bearing industries, but also a large number of small and medium-sized enterprises or home-based workshops. Irregular exhaust emissions and sewage will affect the heavy metal content of the surrounding land (Meuser 2016; Bai et al. 2008). In the following research, the above human factors will be added as the impact factors for analysis.

(2) The effect of GDP on the distribution of soil heavy metal Cd content is also significant, and the interaction with other factors is nonlinearly enhanced, indicating that the distribution of soil heavy metal Cd in Liaocheng is affected by both natural and socioeconomic factors. At present, the analysis of GDP as the only socio-economic factor is slightly singular. In subsequent studies, suitable other economic factors will be selected to participate in the impact factor analysis.

Acknowledgements Sponsored by Shandong Province Green Building Collaborative Innovation Center Team Building Fund Project (LSXT201506) and Shandong Province Professional Degree Postgraduate Teaching Case Library Construction Project.

References

Bai J, Cui B, Wang Q, Gao H, Ding Q (2008) Assessment of heavy metal contamination of roadside soils in Southwest China. Stoch Environ Res Risk Assess 23(3):341–347. https://doi.org/10.1007/s00477-008-0219-5

Chaney RL, Kim WI, Kunhikrishnan A, Yang JE, Ok YS (2016) Integrated management strategies for arsenic and cadmium in rice paddy environments. Geodema 270:1–2

Chen Y, Wang W, Shi H, Wang M, Xu C (2019) Case analysis of influence factors of regional soil heavy metal spatial distribution driving factors. Environ Sci Res 32(07):1213–1223

Cheng S (2003) Heavy metal pollution in China: origin, pattern and control. Environ Sci Pollut Res 10:192–198

China Environmental Monitoring Station (1990) Chinese soil element background value. Beijing, China

Dai B, Lv J, Zhan J, Zhang Z, Liu Y, Zhou R (2015) Source, spatial distribution and potential ecological risk assessment of heavy metals in typical industrial cities of Shandong Province. Environ Sci 36(02):507–515

Ding Q, Cheng G, Wang Y, Zhuang DF (2017) Effects of natural factors on the spatial distribution of heavy metals in soils surrounding mining regions. Sci Total Environ 578:577–585. https://doi.org/10.1016/j.scitotenv.2016.11.001

Dong WQY, Cui Y, Liu X (2001) Instances of soil and crop heavy metal contamination in China. Soil Sedim Contam Int J 10(5):497–510. https://doi.org/10.1080/20015891109392

Du Z, Xu X, Zhang H, Wu Z, Liu Y (2016) Geographical detector-based identification of the impact of major determinants on aeolian desertification risk. PLoS ONE 11(3):e0151331. https://doi.org/10.1371/journal.pone.0151331

Forstner U, Ahif W, Calmano W (1990) Sediment criteria development—contributions from environmental geochemistry to water quality management. Springer, Berlin

Fu W, Liu Y, Tang Q, Cao J, Zhang B (2009) Study on heavy metal pollution and agricultural function localization of cultivated soil based on GIS——taking Liaocheng City of Shandong Province as an example. J China Environ Manag Cadre Coll 19(03):79–82

Hui N (2017) Excessive use of pesticides and fertilizers is worrying. Make a real move to extend soil life and improve soil quality. Chinese National People's Congress 15:47

Li H, Shao Z (2019) Overview of spatial interpolation analysis algorithms. Appl Comput Syst 28(7):1–8

Li Y, Han P, Ren D, Luo N, Wang J (2017) Analysis of factors affecting heavy metals in farmland soil based on geographical detectors. Chin Agric Sci 50(21):4138–4148

Liu Y, Li Z, Zhang B, Cao J (2010) Study on the contents and spatial distribution characteristics of trace elements in soil of Liaocheng City. Jiangsu Agric Sci 4:372–374

Liu Y, Ma C, Cao J, Fu W (2013a) Present situation of heavy metal pollution in soil of Liaocheng City and its potential risk assessment. J Liaocheng Univ (Nat Sci Ed) 26(02):73–77 + 94

Liu Q, Li M, Duan J, Wu H, Hong X (2013b) Analysis of factors affecting the content of lead and cadmium in farmland by geographical weighted regression model. J Agric Eng 29(03):225–234 + 300

Luo Q, Zhang J, Jiang L, Lu C, Guo N, Zhang Q, Li W (2017) Heavy metal content and pollution evaluation of soil in the waterfront zone of Liaocheng City. Ecol Sci 36(01):209–214

Lv J, Liu Y, Zhang Z, Dai J (2013) Factorial kriging and stepwise regression approach to identify environmental factors influencing spatial multi-scale variability of heavy metals in soils. J Hazard Mater 261:387–397

Makino T, Maejima Y, Akahane I, Kamiya T, Takano H, Fujitomi S, Ibaraki T, Kunhikrishnan A, Bolan N (2016) A practical soil washing method for use in a Cd-contaminated paddy field, with simple on-site wastewater treatment. Geodema 270:3–9

Meuser H (2016) Causes of soil contamination in the urban. Contam Urban Soils. https://doi.org/10.1007/978-90-481-9328-8_3

Michaela Z, Raimund P, Iva JC (2019) Field-tests versus laboratory methods for determining metal pollutants in soil extracts. Soil Sedim Contam. https://doi.org/10.1080/15320383.2019.1670136

Ren Z, Xiao R, Zhang Z, Lv X, Fei X (2019) Risk assessment and source identification of heavy metals in agricultural soil: a case study in the coastal city of Zhejiang Province, China. Stoch Environ Res Risk Assess 33(11–12):2109–2118. https://doi.org/10.1007/s00477-019-01741-8

Wang J, Xu C (2017) Geodetector: principles and prospects. J Geogr Sci 72(01):116–134

Wang JF, Li XH, Christakos G, Liao YL, Zhang T, Gu X, Zheng XY (2010) Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun region, China. Int J Geogr Inf Sci 24(1):107–127

Wang JF, Zhang TL, Fu BJ (2016) A measure of spatial stratified heterogeneity. Ecol Ind 67:250–256

Webster R, Oliver M (2001) Geostatistics for environmental scientists. Wiley, New York

Xu M, Zhou S, Wang X, Wu S, Cao W, Zhang H (2010) The impact of social and economic development on the accumulation of heavy metals in soil in a typical area of the Yangtze River Delta. Geogr Sci 6:81–86

Xu J, Meng J, Liu X, Shi J, Tang X (2018) Prevention and control of heavy metal pollution in farmland soils and food security in China. Chin Acad Sci 2:153–159

Yang Y, Tie B, Zhang P, Chen Y, Bai M (2011) Effects of rainfall and vegetation cover on soil heavy metal loss. J Soil Water Conver 25(1):39–42+46

Yang Q, Li Z, Lu X, Du Q, Lei H, Jun B (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

Yin L, Zhang B, Li A, Kang Y, Liu J, Zhang H et al (2014) Effects of soil pH on the behavior of heavy metals in soil. Liaoning Chem Ind 7:865–867

Zhang X, Zhong T, Liu L, Ouyang X (2015) Impact of soil heavy metal pollution on food safety in China. PLoS ONE. https://doi.org/10.1371/journal.pone.0135182

Zhang J, Dong J, Liang Q, Yang N, Geng Y (2019) Detection of factors affecting heavy metal pollution in soils of Baoji City and its source analysis. Environ Sci 40(08):3774–3784

Zhou D (2019) Soil Environmental Remediation Alliance. [Expert opinion], Researcher, Nanjing. Institute of Soil Science, Chinese Academy of Sciences: Impact of temperature increase on heavy metal uptake by crops on contaminated soil. https://www.sohu.com/a/331073127_712505