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Spatial Distribution and Influencing Factors of Soil Heavy Metals in Honghe Prefecture Based on Geodetector

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Abstract

Honghe Prefecture in Yunnan Province is a typical geological high-background area, where excessive soil heavy metal contents have posed adverse impacts locally. This study adopted geodetector and spatial interpolation techniques to explore the spatial distribution and influencing factors of six soil heavy metals, namely cadmium (Cd), lead (Pb), copper (Cu), zinc (Zn), chromium (Cr) and arsenic (As). The results showed that the average contents of the six heavy metals in the study area all exceeded the soil element background values of Yunnan Province. Spatially, high-value areas of the six heavy metals were mainly concentrated in the central part of the region. Geodetector analysis revealed that soil pH, GDP and population (POP) were the dominant factors affecting soil heavy metals. The interaction detector indicated that the interaction of various factors presented either non-linear enhancement or bivariate enhancement. The combination of soil organic matter and POP exerted the strongest interactive effect on Pb. This study clarifies the influencing factors of soil heavy metals in the region, and provides scientific assessment methods and decision support for other similar high-background areas, possessing important scientific value and practical significance.

Keywords

Heavy Metal Pollution, GIS, Source Apportionment, Influencing Factors, Geodetector

1. Introduction

1.1. Research Background

Soil heavy metal pollution is a global environmental issue. With the acceleration of industrialization and urbanization, heavy metal concentrations in soil continue to rise, posing serious threats to ecosystems and human health. Soil heavy metal pollution primarily refers to the concentration of heavy metals (such as lead, cadmium, mercury, and arsenic) exceeding natural background levels, thereby endangering ecological environments and public health. The sources of heavy metals are diverse, including industrial emissions, agricultural activities, and urban development (Xu et al., 2023). Heavy metal pollution is characterized by potential biological toxicity, bioaccumulation, and difficulty in remediation (Huang et al., 2017; Zhang et al., 2020; Liang et al., 2019). At the same time, due to its high toxicity, potential latency and pathogenicity, it has drawn great attention and widespread concern from relevant social fields (Sun et al., 2010; Li et al., 2020; Zhang et al., 2022; An et al., 2016).

Soil heavy metal pollution is a complex environmental issue influenced by various factors. Understanding these influencing factors is crucial for formulating effective strategies for soil pollution control and remediation. Currently, research on heavy metal pollution mainly focuses on soil pollution characteristics, health risks and environmental risks associated with pollution, while there is relatively less research on the main factors contributing to pollution. By comprehensively considering factors such as soil properties, annual average temperature, population distribution, soil pH, and soil organic matter in different regions, we can better understand the mechanism of soil heavy metal pollution, identify the sources of pollution, determine the main influencing factors, and make subsequent soil heavy metal pollution remediation or risk control measures more targeted. This will help better control soil pollution, reduce economic costs, and understand the essence and patterns of heavy metal pollution, thereby providing a solid theoretical foundation for subsequent research and practice.

1.2. Research Progress at Home and Abroad

1.2.1. Spatial Distribution Characteristics of Soil Heavy Metals

The distribution of heavy metals in soil is divided into profile distribution characteristics and horizontal distribution characteristics.

The distribution characteristics of soil heavy metal pollution are that it usually accumulates in the surface layer of the soil. The heavy metals in the surface layer undergo vertical migration through gravity, precipitation, and irrigation leaching. A large number of studies have found that the content of heavy metals in the profile is significantly higher than the crustal background value and the regional background value, indicating that heavy metals have also caused pollution to the deep soil layers of the profile (Ettler et al., 2005). Generally, the content of heavy metals in the soil of the smelting area and its surrounding sections decreases as the depth of the section increases. Most of the heavy metals remain in the surface layer of the soil (Nemati et al., 2011). However, some profiles are the opposite. The content of heavy metals in the deep soil is much higher. Kierczak et al. conducted research on industrial plots in Poland and found that the waste dump sites were covered by vegetation and formed new soil layers. The heavy metal pollution in the deep soil was even more severe (Kierczak et al., 2013). The downward infiltration and migration of heavy metals in the soil profile cannot be ignored. Studying the distribution characteristics of heavy metals in the soil profile is beneficial for protecting the safety of groundwater and provides a scientific basis for risk prediction. Heavy metals in the soil will migrate downward through various pathways, such as rainfall infiltration, mechanical disturbance caused by farming, and soil biological activities (Ettler et al., 2005). It is also influenced by a series of factors such as soil pH, organic matter, land use type, the form and type of heavy metal presence, and iron-aluminum-manganese oxides (Citeau et al., 2003). This includes various processes such as the precipitation, hydrolysis, ion exchange, and adsorption-desorption of heavy metals in soil.

The main influencing factors for the distribution characteristics of soil heavy metal levels are wind direction and distance. Heavy metals can accumulate on the soil surface through atmospheric deposition. Generally, the areas with the main wind direction have higher heavy metal content, showing a long-axis diffusion distribution pattern. The content of soil heavy metals is often negatively correlated with the distance from the smelting production area, and decreases as the distance from the plot increases (Ettler, 2016). It is manifested as a circular or band-like distribution centered around pollution sources such as exhaust gas and waste dump sites (Feng et al., 2006). The horizontal migration and diffusion of soil heavy metals are also influenced by surface runoff, land use types, slope, and particle pollutant particle size. The particle size of the pollutant particles in smelting dust is an important factor determining the diffusion distance of heavy metals under the action of wind. Among them, mining usually produces fine particles with a size of less than 2 μm, while the smelting process mostly generates ultrafine particles with a size of less than 0.5 μm, and the diffusion distance is relatively longer (Csavina et al., 2014).Chang Sha (Chang et al., 2017), Yang Muqing (Yang et al., 2017), and others all conducted analyses on the distribution of heavy metals around the factory. The results of the two sets of experiments showed that the heavy metals mainly accumulated in the main wind direction zone, spreading outwards from the factory to the periphery, with a decreasing trend in the content of heavy metals.

1.2.2. Influencing Factors of Heavy Metals

Understanding the spatial pattern and controlling factors is of great significance for protecting ecosystems and human health. However, due to the complex influence of various factors, the spatial autocorrelation of heavy metals in the soil is relatively weak, making the prevention and control measures for soil pollution more difficult (Zhao et al., 2011).

Studies have shown that the content of heavy metals in the soil is affected by both natural and human factors. Natural factors mainly include parent rock (type), soil formation process, soil composition, soil physical and chemical properties, etc., while human factors mainly include agricultural activities, traffic pollution, and industrial and mining activities, etc. (Fu, 2014; Alloway, 1995; Liang et al., 2017; Wei et al., 2018).

Natural factors such as pH value affect the content of soil heavy metal elements by influencing their activity. The activity of most heavy metal cations significantly increases as the pH value decreases, causing more heavy metal elements to migrate and resulting in a decrease in the content of adsorbed-fixed heavy metal elements in the soil. That is, the heavy metal content in the soil often shows a significant positive correlation with pH (Martinez & Motto, 2000). Yue Jianhua (Yue, 2012) found that in the Changsha-Zhuzhou-Xiangtan area of Hunan Province, when the soil pH is lower than 7.5, the contents of Cu, Zn, Cr, Cd, Pb, and Ni increase significantly with the increase of pH, while when the pH is higher than 7.5, the results are completely opposite.

Human factors, with the continuous development of the economy and society, human activities such as industrial production, transportation, and agriculture have caused significant enrichment of heavy metals in the soil, often exceeding the contribution of natural sources to the heavy metal content (Chen et al., 2005).

The commonly used pollution source analysis methods in current research are mainly divided into two categories: source identification and source interpretation. Source identification mainly identifies the categories of heavy metal pollution sources, while source interpretation estimates the contribution rate of each source (Zhang et al., 2007). Usually, the two methods are combined, first identifying the main causes, and then calculating the contribution of the pollution source to the pollutant. Source identification mainly includes enrichment factor method, geostatistical spatial analysis and other statistical analysis methods. Some studies have used enrichment factor analysis to identify the influencing factors of heavy metal effects and found that human activities led to the enrichment of copper and lead in the soil (Sun et al., 2013). By integrating multiple indicators (such as enrichment factor, geological accumulation index, etc.) and combining the spatial distribution of pollution to analyze the impact of human factors on metal pollution in river sediments (Islam et al., 2015).

The Geographical Detector Method (GDM) is a better choice for exploring the controlling factors of soil heavy metal accumulation. GDM can study the relative contribution of a single factor to an independent variable based on the spatial variability of pollutants. If a factor causes soil pollution, the pollution distribution of the soil will show a spatial distribution similar to this influencing factor. Geographical Detector has been applied to analyze the controlling factors of the spatial patterns of various geographical phenomena. Therefore, the geographical detector can more comprehensively explain the relationship between data and type factors and the distribution of soil heavy metals, and quantify the relative contribution size of influencing factors in the analysis of the spatial distribution factors of heavy metal distribution.

1.2.3. Sources and Hazards of Heavy Metals

Currently, both domestic and international studies unanimously agree that: The heavy metal elements in soil mainly come from two aspects: natural soil-forming parent materials and human economic activities. In the natural environment, rocks undergo long-term weathering and erosion by rainwater to form soil. Most elements in the soil are similar to the soil-forming parent rocks, and the content of heavy metal elements in the soil basically inherits the basic chemical characteristics of the soil-forming parent rocks. Therefore, the content and type of heavy metals in soil are influenced by both natural soil-forming parent materials and the combined effects of various factors such as human activities.

Heavy metals in soil not only damage the growth environment of plants, but also can be absorbed by plants, resulting in a biological accumulation phenomenon. Through the food chain, they enter the human body and accumulate continuously. When the content of heavy metals entering the body is too high and exceeds the maximum tolerance limit of the human body, various diseases will be induced, causing damage to the liver, kidneys, intestines, stomach, nervous system, etc. of the human body. Severe cases may even cause deformity and cancer.

1.3. Research Objectives and Significance

Further, the correlation analysis and geographical detector combination method are used to analyze the factors influencing heavy metals. This study innovatively combines spatial analysis technology, systematically assesses the pollution status and spatial distribution characteristics of heavy metals in the soil of Honghe Prefecture, Yunnan Province, and deeply explores the multi-factor mechanism of the distribution of heavy metals. This not only fills the gap in the research on soil heavy metal pollution in this region, but also provides a scientific assessment method and decision support for other similar high-background-value regions, and has important scientific value and practical significance.

The significance of this study lies in providing benchmark data for environmental management and monitoring in this region. By understanding the influencing factors of heavy metal pollution, the government and environmental protection agencies can formulate corresponding environmental protection policies and measures, prevent and control heavy metal pollution targetedly, protect environmental health, and in-depth analysis of the influencing factors of heavy metal pollution is beneficial to related scientific research, promotes the innovation and application of environmental protection and ecological restoration technologies, and provides scientific basis for environmental governance.

The research on heavy metal pollution has important theoretical and practical significance. It promotes the development of environmental science research. The research on heavy metal pollution provides rich research materials for the environmental science field, promotes in-depth understanding of pollutant behavior, migration and transformation processes, and promotes the development of environmental monitoring and assessment technologies.

2. Materials and Methods

2.1. Overview of the Study Area

Honghe Prefecture is located in the south of Yunnan Province and the southwest of Honghe Hani and Yi Autonomous Prefecture, ranging from 101˚49'E to 102˚37'E and 23˚05'N to 23˚27'N. Located in the low-latitude region, it has a typical subtropical mountain monsoon climate and occupies an important geographical position in regional ecological research. The altitude varies from 259 m to 2745.8 m with a large relative elevation difference. The annual average temperature is between 11.2˚C and 23.4˚C, and the annual precipitation ranges from 800 mm to 1900 mm (Kong et al., 2022). The unique natural geographical conditions and socioeconomic characteristics of Honghe Prefecture make it a representative research area for exploring the influencing factors of heavy metal pollution. Research on heavy metal pollution in this area is of great significance for local ecological environmental protection and sustainable development.

2.2. Soil Sampling and Determination

2.2.1. Soil Sampling

A total of 113 soil samples were collected from July to September 2024. Grid sampling was adopted as the primary layout strategy, with densified supplementary sampling implemented in key human-disturbed zones. The grid interval was set to 1.5 - 2.0 km for valley flat farmlands and 2.0 - 3.0 km for mountain sloping farmlands, while extra sampling sites were arranged around industrial mines and towns with intensive anthropogenic activities. All sampling points were located at least 200 m away from potential pollution sources including roads and mining sites. The sampling sites covered three major agricultural land types: paddy fields, dry farmlands and orchards. Sample quantities were allocated proportionally based on the area share of each land type, with each category accounting for no less than 15% of all sampling points. Sampling was prioritized at the geometric center of each farm plot. After removing surface vegetation and debris, topsoil samples at the depth of 1 - 20 cm were collected using the mixed sampling method. Each soil sample weighed about 1 kg and was mixed from 3 - 5 sub-samples. All samples were packed and labeled, and field information including coordinates and soil types was recorded with photos taken on site.

After registration and numbering, the collected samples were air-dried indoors. The air-dried soil was ground and divided into two parts by the quartering method: one for the determination of total heavy metal contents, and the other for the analysis of soil physicochemical properties. The processed samples were stored in plastic bags with clear labels indicating sample number, sampling location, soil type and sieve aperture.

2.2.2. Sample Analysis

The contents of Cd, Pb, Cu, Zn, Cr and As in soil were determined by different instruments: flame atomic absorption spectrophotometer and graphite furnace atomic absorption spectrophotometer (Shimadzu AA6880) for Cd, Pb, Cu, Zn and Cr, and atomic fluorescence spectrophotometer (Haiguang AFS-230E) for As.

- Soil pH: Measured by pH meter with a solid-liquid ratio of 1:2.5. The mixture was fully stirred and balanced for 30 minutes before detection.
- Soil organic matter: Determined by the potassium dichromate external heating method (NY/T 1121.6-2006). The sample was heated in an oil bath at 180˚C for 5 minutes. The remaining potassium dichromate was titrated with ferrous sulfate solution, and the organic matter content was calculated according to the consumption of potassium dichromate.
- Heavy metal detection standards: The determination of total Cd and Pb referred to Soil Quality—Determination of Lead and Cadmium—Graphite Furnace Atomic Absorption Spectrophotometry (GB/T 17141-1997). Total Cu, Zn and Cr were tested in accordance with GB/T 17138-1997 (Flame Atomic Absorption Spectrophotometry). Total As was determined following GB/T 22105 (Atomic Fluorescence Spectrophotometry).

The 0.200 g air-dried soil samples passing through 0.149 mm sieve were weighed and placed in a PTFE digestion tank. Cd, Pb, Cu, Zn and Cr were digested by 5 mL HNO3 + 2 mL HF mixed acid microwave digestion. The program was set at 120˚C for 5 min, 160˚C for 10 min, and 190˚C for 20 min. After complete cooling, the acid was removed to near dryness (avoiding Pb to form insoluble fluoride precipitate) by an electric heating plate at a temperature of 120˚C - 130˚C, and then diluted with 1% dilute nitric acid to 25 mL to be measured.

The digestion procedure for As was as follows: 0.200 g of air-dried soil samples sieved through a 0.149 mm nylon sieve were mixed with 5 mL aqua regia ($HCl:HNO_3$ = 3:1), followed by digestion in a water bath at 95˚C for 2 h. After cooling to room temperature, 5 mL of mixed reducing solution containing 5% thiourea and 5% ascorbic acid was added. The solution was subsequently diluted to 25 mL with 10% HCl, fully shaken, and kept standing for 30 min prior to instrumental analysis.

According to HJ 168-2020 "Technical guideline for the development of environmental monitoring analytical method standards" (Ministry of Ecology and Environment of the People's Republic of China, 2020) the instrumental detection limits were calculated based on 11 consecutive measurements of blank solutions. The instrumental detection limits for Cd, Pb, Cu, Zn, Cr and As were 0.002, 0.010, 0.005, 0.008, 0.010 and 0.003 mg/kg, respectively, all of which were much lower than the measured concentrations of soil samples. Both reagent blanks and full-process blanks were prepared throughout the experiment, with one blank group arranged for every 20 test samples. The concentrations of the six heavy metals in all blank solutions were below the corresponding instrumental detection limits, ruling out contamination interference from experimental reagents, digestion vessels and ambient laboratory environment.

Two portions of the national first-class certified soil reference material GSS-25 were incorporated into each batch of digested samples for synchronous pretreatment and measurement. The relative errors between the measured values and certified reference values for all elements were within ±8%, verifying the satisfactory accuracy of the analytical procedure.

Recovery tests were performed at three concentration levels (low, medium and high). The recoveries of Cd, Pb, Cu, Zn, Cr and As ranged from 90.3% - 106.4%, 86.7% - 107.1%, 90.3% - 102.8%, 88.6% - 108.1%, 90.5% - 105.3% and 92.1% - 106.5%, respectively. All recovery values fell within the acceptable range of 85% - 115%, demonstrating negligible element loss and absence of exogenous contamination during digestion.

For precision control, one sample was randomly selected from every 10 soil samples to prepare duplicate subsamples. The acceptable relative deviations were defined as ≤5% for samples with metal concentrations ≥1 mg/kg, ≤10% for 0.1 - 1 mg/kg, and ≤15% for concentrations below 0.1 mg/kg. The relative deviations of all duplicate samples met the above criteria.

2.3. Geodetector

The geophysical detector is a tool based on the theory of spatial differentiation, using spatial statistical methods to detect and quantitatively analyze the interaction effects among influencing factors (Wang et al., 2017). This model consists of four sub-models: factor detector, ecological detector, risk detector, and interaction detector. In this study, the factor detector and interaction detector are mainly utilized. Among them, the factor detector is the core part. The model is as follows:

$$q = 1 - \frac{\sum_{i=1}^{m} n_{D,i}\sigma_{D,i}^2}{n\sigma^2}$$

Table 1. Types of interaction between two covariates.

criterion	interaction
q (X1 ∩ X2) < Min (q (X1), q (X2))	Nonlinear attenuation
Min (q (X1), q (X2)) < q (X1 ∩ X2) < Max (q (X1), q (X2))	Single-factor nonlinear attenuation
q (X1 ∩ X2) > Max (q (X1), q (X2))	Two-factor enhancement
q (X1 ∩ X2) = q (X1) + q (X2)	independence
q (X1 ∩ X2) > q (X1) + q (X2)	Nonlinear enhancement

In the formula, q represents the explanatory power of the influencing factor for the spatial distribution of the ecological risk of heavy metal pollution sources, n represents the total number of research area units, represents the number of units in the i-th partition of factor D, σ represents the total standard deviation of the dependent variable, and represents the standard deviation of the i-th partition of factor D. The size of q indicates the strength of spatial differentiation; q ∈ [0, 1]. As shown in **Table 1**, when the q value is closer to 1, the spatial heterogeneity is stronger, and vice versa. The interaction detector measures the explanatory power of two factors for the ecological risk of the pollution source. If the value is closer to 1, it indicates a more obvious interaction effect (Gao et al., 2021). The geographical detector is good at analyzing categorical quantities and can also be used for statistical analysis of measurement-type data using the geographical detector. Therefore, the geographical detector can detect both numerical data and qualitative data, which is one of its major advantages.

2.4. Data Collection and Processing

The spatial distribution data of China's elevation (DEM) is derived from the SRTM (Shuttle Radar Topography Mission) data collected by the US Space Shuttle Endeavour. The spatial grid dataset of China's GDP distribution is sourced from the Resource and Environment Science Data Registration and Publication System (Xu, 2017a). The annual spatial interpolation dataset of meteorological elements in China is derived from the Resource and Environment Science Data Registration and Publication System (Xu, 2022). The spatial grid dataset of China's population distribution is obtained from the Resource and Environment Science Data Registration and Publication System (Xu, 2017b). The data of the influencing factors under investigation is sourced from the Resource and Environment Science Data Platform (https://www.resdc.cn/Default.aspx).

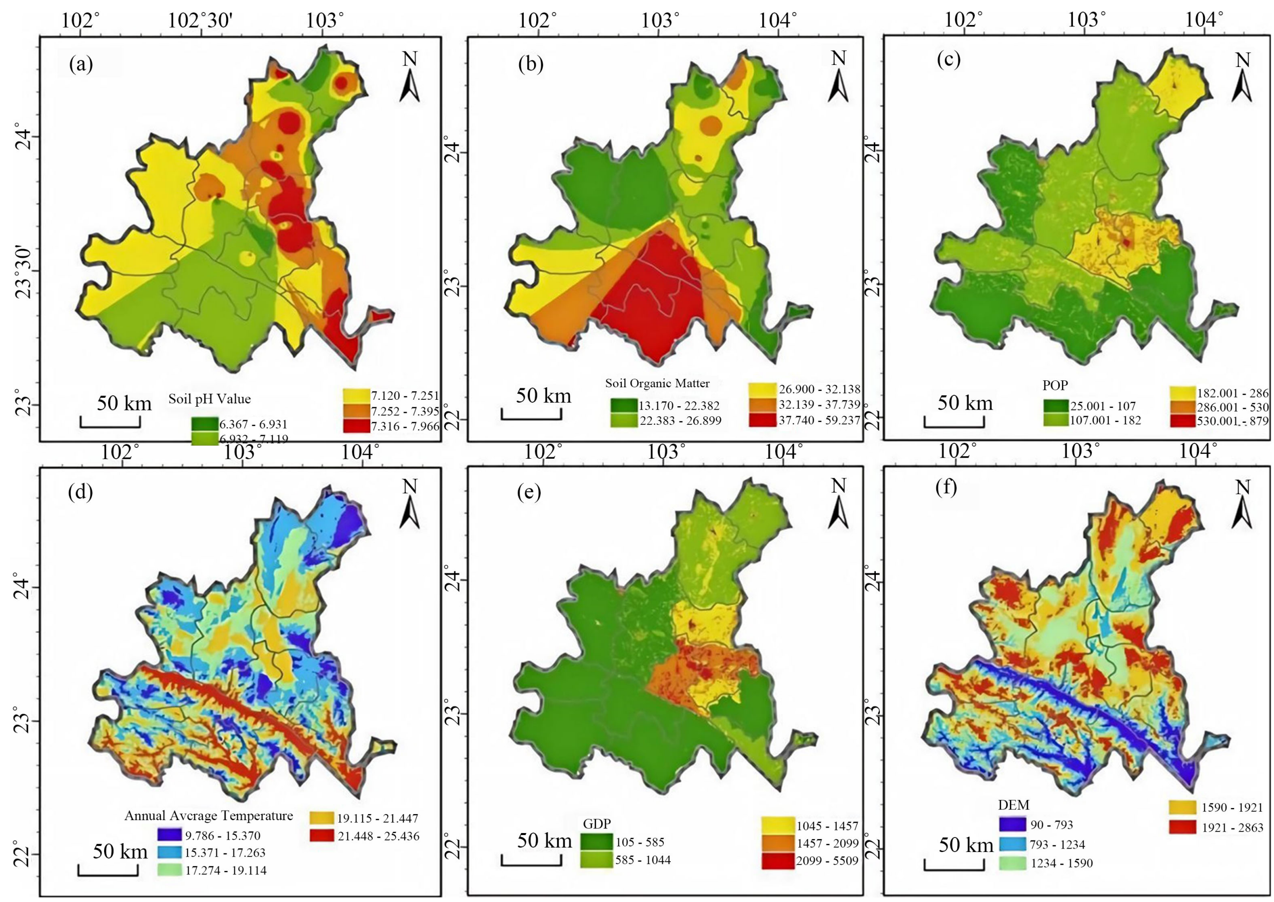

Figure 1. Distributions of various influencing factors.

After the sampling data were processed by Microsoft Excel 2010, the descriptive statistics of soil heavy metal contents were conducted using SPSS 20.0 statistical software. The natural and human influencing factors of soil heavy metal spatial distribution were studied by using the geographical detector method. If a certain independent variable has a significant impact on a certain dependent variable, then the spatial distribution of the independent variable and the dependent variable should be similar (Wang et al., 2017). In this study, soil pH (X1), soil organic matter (X2), population-kilometer grid distribution POP (X3), annual average temperature TEM (X4), GDP (X5), DEM (X6), etc. were used as soil heavy metal influencing factors. The distribution status of each factor is shown in **Figure 1**.

Six continuous explanatory variables were selected in this study, including soil pH (X1), soil organic matter (X2), population density (POP, X3), annual mean temperature (TEM, X4), GDP (X5), and digital elevation model (DEM, X6). Since the geographical detector model only accepts categorical input variables, all continuous predictors were subjected to discretization processing. The Jenks natural breaks classification method was adopted for grading, which partitions intervals based on inherent data distribution characteristics. Compared with equal interval and quantile classification, this approach better fits the spatial differentiation patterns of soil heavy metals.

To verify the robustness of discretization results, grading schemes with 3, 4, 5, 6 and 7 categories were tested separately. The q-statistic values, factor rankings and significance levels of the six heavy metals under different grading numbers were compared. The results indicated that adjusting the category number within the range of 3 - 7 exerted no obvious shift in the rank of core driving factors for each heavy metal. The fluctuation range of q values was limited within 0.09, and no reversal of significance judgment was observed, demonstrating the stability of the grading strategy. Balancing sample quantity and result stability, all six influencing factors were finally classified into five categories, and the discretized datasets were imported into the geographical detector for subsequent calculation.

Inverse distance weighting (IDW) interpolation was adopted in this study to visualize the spatial distribution of soil heavy metals. The IDW algorithm requires no normal distribution of input data and features straightforward calculation. In contrast to ordinary Kriging, IDW can better preserve high-concentration hotspots without excessive smoothing of metal enrichment zones, making it more applicable to sampling datasets from fragmented mountainous farmlands in Honghe Prefecture. Restricted by terrain fragmentation and patchy land use, the 113 sampling points exhibited weak spatial continuity, which led to unstable fitting of the semivariogram required for Kriging interpolation. Cross-validation results further confirmed that IDW yielded lower prediction errors and more accurately reproduced the prominent central enrichment pattern of soil heavy metals across Honghe Prefecture.

3. Results and Discussion

3.1. Descriptive Statistics of Soil Heavy Metals

As shown in **Table 2**, the content ranges of As, Cu, Zn, Pb, Cd and Cr in the study area are 0.12 - 167.09, 9.6 - 969.7, 11.65 - 468.77, 5.58 - 678.07, 0.02 - 7.74, and 7.3 - 513 mg/kg respectively, with the average values being 21.39, 73.3, 142.52, 84.14, 0.7, and 110.35 mg/kg respectively. The average values of all heavy metal elements exceed the background values (Ma, 2012), indicating that there is a certain enrichment trend of these heavy metal elements in the surface soil. All heavy metal elements exceed the screening values for soil pollution risks in agricultural land (Ministry of Ecology and Environment of the People's Republic of China, 2018), suggesting that the current soil heavy metal content poses a relatively high risk to the quality of local agricultural products. The correlation analysis results (**Table 3**) show that the correlation between As content and Pb and Cr content, Cr content and Cu, Pb and Cd content is not significant. The correlation between As content and Zn and Cd content is significantly positive ($P < 0.05$), exhibits an extremely significant positive correlation with Cu concentration ($P < 0.01$), The correlation between Cu content and Zn, Pb and Cd content is extremely significant positive ($P < 0.01$), between Zn content and Pb, Cd and Cr content is extremely significant positive ($P < 0.01$), and between Pb content and Cd content is extremely significant positive ($P < 0.01$). The larger the correlation coefficient, the more similar the sources or distributions of the elements are (Ning et al., 2017).

Table 2. Descriptive statistics of soil heavy metal contents (mg/kg).

Heavy Metal	Minimum	Maximum	Mean	Standard	Deviation (Ma, 2012)	Background (Ministry of Ecology and Environment of the People's Republic of China, 2018)
As	0.12	167.09	21.39	27.3	14.65	25
Cu	9.6	969.7	73.3	103.13	38.38	100
Zn	11.65	468.77	142.52	96.99	92.82	300
Pb	5.58	678.07	84.14	129.26	41.24	170
Cd	0.02	7.74	0.7	1.17	0.1	0.6
Cr	7.3	513	110.35	79.47	72.4	250

Table 3. Correlation analysis of soil heavy metals.

	As	Cu	Zn	Pb	Cd	Cr
As	1					
Cu	0.309**	1				
Zn	0.212*	0.381**	1			
Pb	0.164	0.559**	0.391**	1		
Cd	0.190*	0.421**	0.377**	0.620**	1	
Cr	0.016	0.072	0.260**	0.003	−0.013	1

Note: *indicates significant correlation at $P < 0.05$ level; **indicates extremely significant correlation at $P < 0.01$ level.

3.2. Spatial Distributions of Soil Heavy Metals

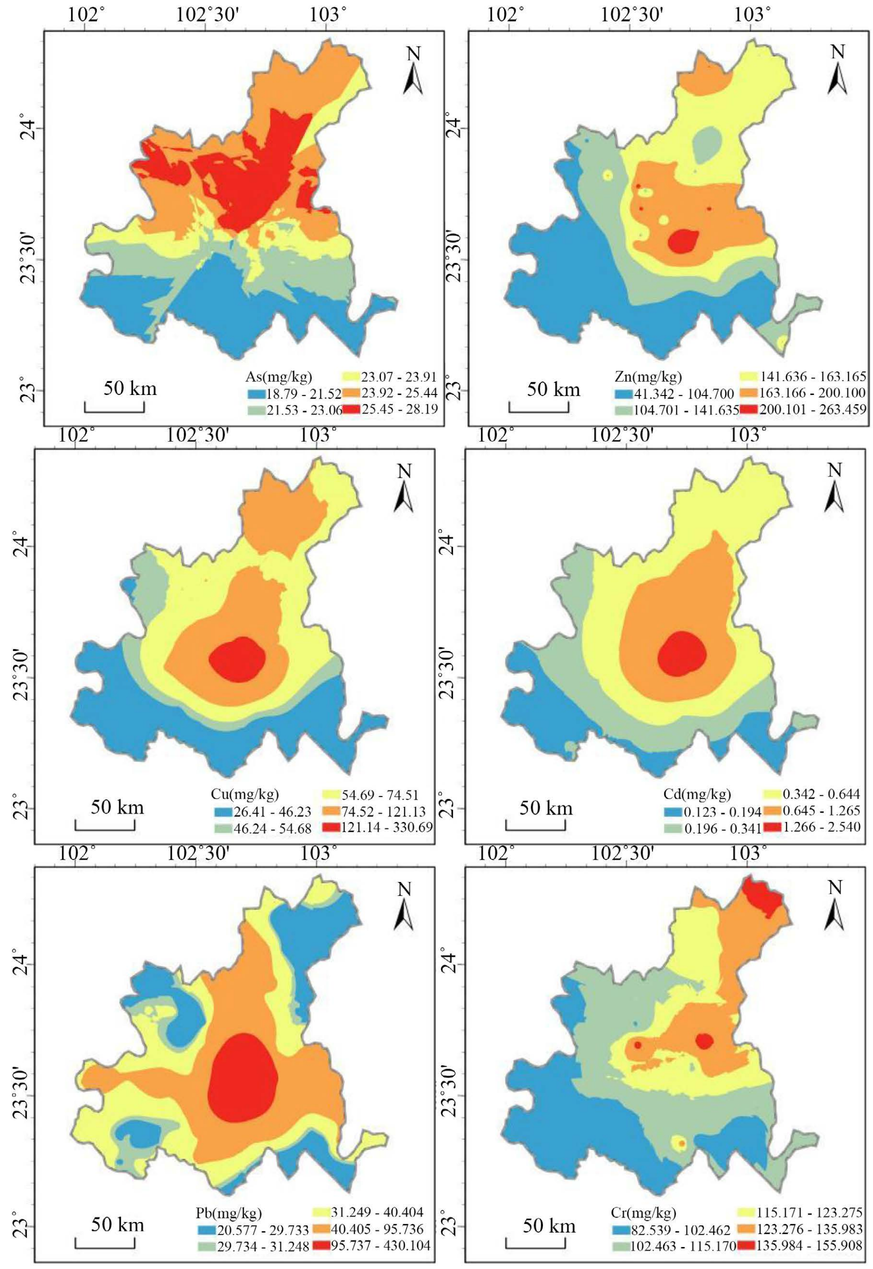

Figure 2. Spatial distributions of soil heavy metals.

The inverse distance weighting (IDW) interpolation method was applied to map the spatial distribution of heavy metals (Figure 2). The six heavy metals presented different spatial distribution patterns:

- High-value areas of As were mainly distributed in the central and northern parts, while low-value areas were in the south, showing a decreasing trend from central-northern areas to the south.
- High-value zones of Cu, Zn, Pb and Cd were all concentrated in the central region. Low-value areas of Cu, Zn and Cd were located in the southern and

western parts, and Pb content decreased gradually from the center to the surrounding areas.

- High-value areas of Cr appeared in the central and northern regions, and low-value areas were in the southwest.

3.3. Influencing Factors of Soil Heavy Metals

This study selected natural factors (soil pH, soil organic matter, annual average temperature, DEM) and anthropogenic factors (population density, GDP) to explore the driving forces of heavy metal spatial distribution. Continuous data were discretized to adapt to the operation requirements of geodetector.

3.3.1. Influence Intensity of Single Factors

The factor detector results (Figure 3 and Table 4) showed that each factor exerted different influences on the spatial distribution of heavy metals:

- Soil pH was the dominant factor for As distribution, with an explanatory power of 0.125.
- GDP was the primary influencing factor for Cu, Zn, Pb and Cd, with explanatory powers of 0.176, 0.361, 0.399 and 0.269 respectively.
- Population density (POP) was the leading factor for Cr distribution, with an explanatory power of 0.098.

Overall, soil pH was the key natural factor, and GDP was the dominant anthropogenic factor affecting soil heavy metal distribution.

Table 4. Influencing factor analysis of soil heavy metals based on geodetector.

	X1	X2	X3	X4	X5	X6
As	0.125**	0.019	0.035	0.020	0.037	0.062
Cu	0.012	0.018	0.147***	0.123**	0.176***	0.072
Zn	0.154**	0.035	0.351***	0.089	0.361***	0.035
Pb	0.019	0.092*	0.289***	0.232***	0.399***	0.114**
Cd	0.061	0.015	0.237***	0.052	0.269***	0.025
Cr	0.060	0.034	0.098**	0.035	0.069	0.036

Note: **There is a highly significant correlation at $p < 0.01$; ***There is an extremely significant correlation at $p < 0.001$.

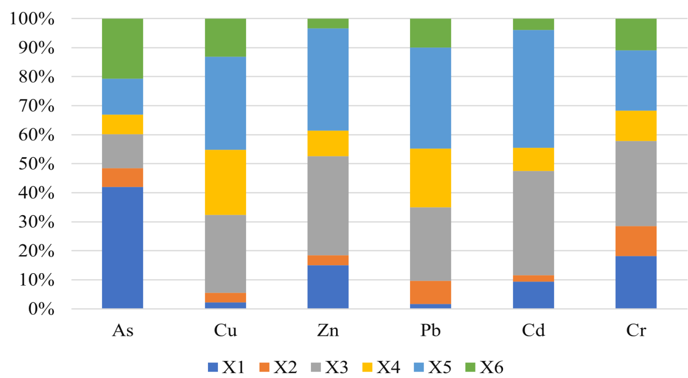

Figure 3. Contributions of influencing factors to soil heavy metal distribution.

3.3.2. Interactive Effects of Factors

In this study, the interaction detector was used to identify the interactive effects of different influencing factors on the spatial distribution of soil heavy metals in the study area. The results showed that the q-values representing the interaction influence between paired factors were all higher than the q-values of individual factors, which mainly manifested as bilinear enhancement and nonlinear enhancement. This indicates that the interaction between two factors exerts a stronger influence than a single factor. The intensity of pairwise factor interactions varied among different heavy metal elements. This paper mainly analyzes the top five factor pairs with the highest influence, as shown in Table 5.

The interaction q-values of X1 ∩ X4, X1 ∩ X6, X4 ∩ X5, X3 ∩ X4 and X1 ∩ X5 on the spatial distribution of As all exceeded 0.3, and the influence value of X1 ∩ X4 reached 0.464.

For Cu, the interaction influences of X1 ∩ X5, X2 ∩ X3, X1 ∩ X2, X1 ∩ X3 and X3 ∩ X4 were all above 0.4, with X1 ∩ X5 reaching 0.593.

For Zn, the interaction q-values of X1 ∩ X3, X1 ∩ X5, X2 ∩ X5, X5 ∩ X6 and X4 ∩ X5 were all higher than 0.4, and the value of X1 ∩ X3 was up to 0.574.

For Pb, the interaction influences of X2 ∩ X5, X1 ∩ X5, X5 ∩ X6, X4 ∩ X5 and X2 ∩ X3 all exceeded 0.6, and X2 ∩ X5 attained the maximum value of 0.790.

For Cd, the interaction q-values of X1 ∩ X2, X5 ∩ X6, X4 ∩ X5, X3 ∩ X4 and X3 ∩ X6 were all greater than 0.4, among which X1 ∩ X2 reached 0.608.

For Cr, the interaction influences of X5 ∩ X6, X2 ∩ X6, X1 ∩ X2, X4 ∩ X5 and X3 ∩ X4 were all above 0.2, and X5 ∩ X6 reached 0.311.

The factor pair X4 ∩ X5 appeared five times, showing the highest frequency among all factor pairs. It can be concluded that X4 ∩ X5 (annual average temperature ∩ GDP) exerted a prominent impact on the spatial distribution of soil heavy metals in the study area.

In terms of the explanatory power of interactions among major influencing factors for heavy metal concentrations, the top five factor pairs were ranked in descending order of occurrence frequency as follows:

X4 ∩ X5 (5) > X3 ∩ X4 (4) = X1 ∩ X5 (4) = X5 ∩ X6 (4) > X1 ∩ X2 (3) > X2 ∩ X3 (2) = X1 ∩ X3 (2) = X2 ∩ X5 (2) > X1 ∩ X4 (1) = X1 ∩ X6 (1) = X3 ∩ X6 (1) = X2 ∩ X6 (1)

Table 5. Top 5 paired factors and their interaction influence on soil heavy metals.

HeavyMetal	1	2	3	4	5
As	X1 ∩ X4 (0.464)	X1 ∩ X6 (0.447)	X4 ∩ X5 (0.367)	X3 ∩ X4 (0.326)	X1 ∩ X5 (0.303)
Cu	X1 ∩ X5 (0.593)	X2 ∩ X3 (0.542)	X1 ∩ X2 (0.515)	X1 ∩ X3 (0.508)	X3 ∩ X4 (0.439)
Zn	X1 ∩ X3 (0.574)	X1 ∩ X5 (0.541)	X2 ∩ X5 (0.468)	X5 ∩ X6 (0.467)	X4 ∩ X5 (0.465)
Pb	X2 ∩ X5 (0.790)	X1 ∩ X5 (0.774)	X5 ∩ X6 (0.703)	X4 ∩ X5 (0.697)	X2 ∩ X3 (0.624)
Cd	X1 ∩ X2 (0.608)	X5 ∩ X6 (0.594)	X4 ∩ X5 (0.591)	X3 ∩ X4 (0.466)	X3 ∩ X6 (0.457)
Cr	X5 ∩ X6 (0.311)	X2 ∩ X6 (0.259)	X1 ∩ X2 (0.252)	X4 ∩ X5 (0.249)	X3 ∩ X4 (0.247)

Note: X1, X2, X3, X4, X5 and X6 represent soil pH, soil organic matter, POP, annual average temperature, GDP and DEM, respectively. The values in parentheses in the table are the corresponding influence q-values.

3.4. Discussion

The results of this study show that the average contents of heavy metals As, Cu, Zn, Pb, Cd, and Cr in the study area all exceeded the background values of 13 heavy metal elements in Yunnan Province. This may be related to agricultural production management processes, such as the application of chemical fertilizers and organic fertilizers, as well as industrial smelting construction. The content of Cd and Cr in phosphorus fertilizers is relatively high, so the use of livestock manure as fertilizer will also bring a large amount of heavy metal elements into the farmland soil. In addition, with the rapid development of cities and the acceleration of industrialization, the content of heavy metals has also exceeded the standard. The contents of Zn and Cd are most affected by GDP and POP, indicating that the pollution sources of Zn and Cd are closely related to human activities. The contents of Cu, Zn, Cd, and Pb show similar spatial distribution characteristics, which is consistent with the results of the correlation analysis.

The single-factor analysis results of the spatial distribution of heavy metals in cultivated soil of the study area using the geodetic detector model show that different factors have varying degrees of influence on the spatial distribution of soil heavy metals. This is consistent with the conclusions obtained from previous analyses of the influencing factors of soil heavy metals in cultivated land (Song et al., 2018). GDP has a significant impact on soil heavy metals. During the process of economic development and GDP growth, some related activities may cause an increase in heavy metal content, such as mineral extraction and smelting in industrial production, emissions from manufacturing, the use of chemical fertilizers and pesticides in agricultural activities, and irrigation with sewage. In transportation and infrastructure construction: vehicle exhaust emissions, road and construction activities. However, the influence of soil organic matter and DEM on soil heavy metal pollution in this study is relatively small, mainly because the terrain of the experimental area is relatively flat, and the migration of heavy metals is restricted, and the adsorption and fixation of the soil are stable. However, the influence of the annual average on soil heavy metals in this study is relatively small, possibly because the experimental area spans fewer latitudes and is affected by terrain and topography, resulting in a smaller impact of the annual average temperature on heavy metal pollution.

The analysis results of the interaction detector show that the factor with the highest explanatory power for heavy metal elements comes from both natural and human factors. For the six heavy metal elements, the explanatory power of interaction is significantly higher than that of single factors, and from the interaction results, the interaction between human factors and natural factors is stronger than the interaction between natural factors or among human factors. The interaction of natural factors and human factors on spatial differentiation has caused the uneven distribution of heavy metals in space.

The geographical detector is a statistical model used for spatial analysis, mainly used to detect spatial hierarchical heterogeneity and reveal the driving factors behind it. However, it also has many shortcomings, such as: data types are limited, and independent variables usually require type values, such as dividing land use types into cultivated land, forest land, and construction land categories instead of numerical values. This limits the direct application of some continuous data and requires discretization processing if used, which may result in the loss of data information. Moreover, the application scenarios are limited. In some fields that require high precision and detailed analysis, such as micro-scale ecosystem research and high-precision urban planning and design, the geographical detector may not provide sufficient detailed and accurate information.

4. Conclusions

1) The average contents of As, Cu, Zn, Pb, Cd and Cr in the study area all exceeded the soil background values of Yunnan Province. Reasonable selection and application amount control of chemical fertilizers should be emphasized in future agricultural production.

2) Spatially, high-value areas of As and Cr were concentrated in the central and northern parts. Cu, Zn, Pb and Cd were mainly enriched in the central region of the study area, showing a decreasing trend from the center to the surrounding areas.

3) Soil pH (natural factor), GDP and population density (anthropogenic factors) were the main factors controlling the spatial distribution of soil heavy metals. The interactive effect of any two factors was stronger than the effect of a single factor, presenting bivariate enhancement or non-linear enhancement.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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