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Article

Temporal–Spatial Distributions and Influencing Factors of Heavy Metals As, Cd, Pb, and Zn in Alluvial Soils on a Regional Scale in Guangxi, China

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Abstract: Understanding the temporal–spatial distribution and influencing factors of heavy metals on a regional scale is crucial for assessing the anthropogenic impacts and natural variations in elemental geochemical behavior. This study evaluated the spatial distributions of the heavy metals As, Cd, Pb, and Zn as well as the driving mechanisms over the past 31 years in Guangxi, China, using three geochemical baseline projects (the Environmental Geochemical Monitoring Network Project (EGMON) project 1992–1996; the Geochemical Baseline (CGB) 1 project 2008–2012; and the CGB2 project 2015–2019). By calculating the variable importance using the random forest algorithm, it was found that natural factors are the primary drivers of the spatial distribution of heavy metals in the EGMON project, especially precipitation for As, the digital elevation model (DEM) for Cd and Pb, and temperature for Zn. Surface alluvial soils showed obvious heavy metal enrichment in the CGB1 project, with the gross domestic product (GDP) driving the spatial distribution of all heavy metals. In addition, the anomalous intensity and range of heavy metals in the CGB2 project decreased significantly compared with the CGB1 project, especially owing to the normalized difference vegetation index (NDVI) as a positive anthropogenic factor that improves the degree of rocky desertification, thus reducing the heavy metal contents of As and Pb, and the precipitation promoting the decomposition of Fe–Mn concretions and thus the migration of Cd and Zn. This research promotes an understanding of anthropogenic and natural influences on the spatiotemporal distribution of heavy metals and is of great significance for environmental monitoring and governance.

Keywords: heavy metals; alluvial soil; spatiotemporal variations; driving factors; geochemical baseline projects

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1. Introduction

Heavy metals are harmful pollutants that are covert, persistent, irreversible, and easily enter the human body through the food chain, causing damage and pathological changes in organs and thus threatening human health [1–5]. Heavy metals are widely recognized as a global environmental threat [6–8]. Therefore, it is of great significance to study the spatiotemporal distributions of heavy metals to monitor anthropogenic disturbances and naturally occurring changes. However, previous studies on the spatiotemporal distributions of heavy metals have mostly been based on data from two periods and have mostly been conducted at the local scale [9–11]. Moreover, previous studies have mainly focused on spatial–temporal change characteristics, ignoring the quantitative evaluation of the main driving factors of spatiotemporal changes [12,13].

China has conducted three environmental geochemical baseline projects aimed at monitoring the changes in concentration and spatial distribution of geochemical elements caused by anthropogenic activities, climate change, and geological processes, thus providing a quantitative scale for environmental change, including the Environmental Geochemical Monitoring Network Project in 1992–1996 (EGMON) [14,15] and China's first and second Geochemical Baseline projects in 2008–2012 (CGB1) [16] and 2015–2019 (CGB2) [17]. These projects aimed to provide high-resolution and high-quality geochemical baseline data by developing improved sampling and laboratory analysis methodologies. The primary objective of the projects was to establish nationwide geochemical baselines against which future human-induced or natural chemical changes could be recognized and quantified. Samples of alluvial soil, the most representative sampling medium, which represents the average values of elements and effectively reflects the environmental changes caused by human input in the basin, were collected. Alluvial soils can be used to monitor environmental changes and inputs because the transport processes of pollutants in rivers occur continuously [18]. The similar sample media, analytical methods, and quality controls used by the three projects may provide an unbiased opportunity to quantify these changes [19].

The driving factors of spatiotemporal variations in heavy metals generally include external inputs; the influence of parent materials; and geochemical processes, such as leaching and transformation through surface runoff [20,21]. Heavy metals in soils are sourced from parent materials, the concentrations of which are usually increased by external inputs, whereas both are increased or decreased by geochemical processes, depending on the different elements and environmental conditions [22]. Therefore, identifying the main driving factors and quantifying their influence on the spatiotemporal variations of heavy metals is helpful in determining the sources of heavy metals and providing meaningful information on anthropogenic disturbances and naturally occurring changes [23–25].

Random forest is a highly accurate, adaptable, and interpretable machine learning method that uses a set of decision trees to classify and regress and can incorporate both continuous variables and type variables simultaneously [26]. Moreover, the predictive values of the dependent variables and the relative importance of each variable can be calculated on the basis of the nonlinear relationships between the dependent and independent variables. The random forest method is becoming increasingly popular in many fields, such as geological mapping [27], digital soil mapping [28], and mineral exploration mapping [29].

This study investigated the spatiotemporal distributions and variations of the heavy metals As, Cd, Pb, and Zn in Guangxi, China, a typical province with a widely distributed karst area, and quantified the driving factors impacting heavy metal concentrations at regional scales using a random forest algorithm based on data obtained from three geochemical baseline projects. This research is helpful for understanding the geochemical behavior of heavy metals and quantitatively evaluating anthropogenic disturbances and natural changes over a long period of time.

2. Materials and Methods

2.1. Study Area

The total area of Guangxi province, located in South China (104°26′ E~112°04′ E; 20°54′ N~26°24′ N), is about 23.67×10^4 km^2, and the province has a subtropical monsoon humid climate (Figure 1). The terrain inclines from the northwest to the southeast and is dominated by basins. Karst landforms are widely distributed in central, western, and northwestern Guangxi, covering an area of approximately 9.58×10^4 km^2, accounting for 40.9% of the total area (Figure 2).

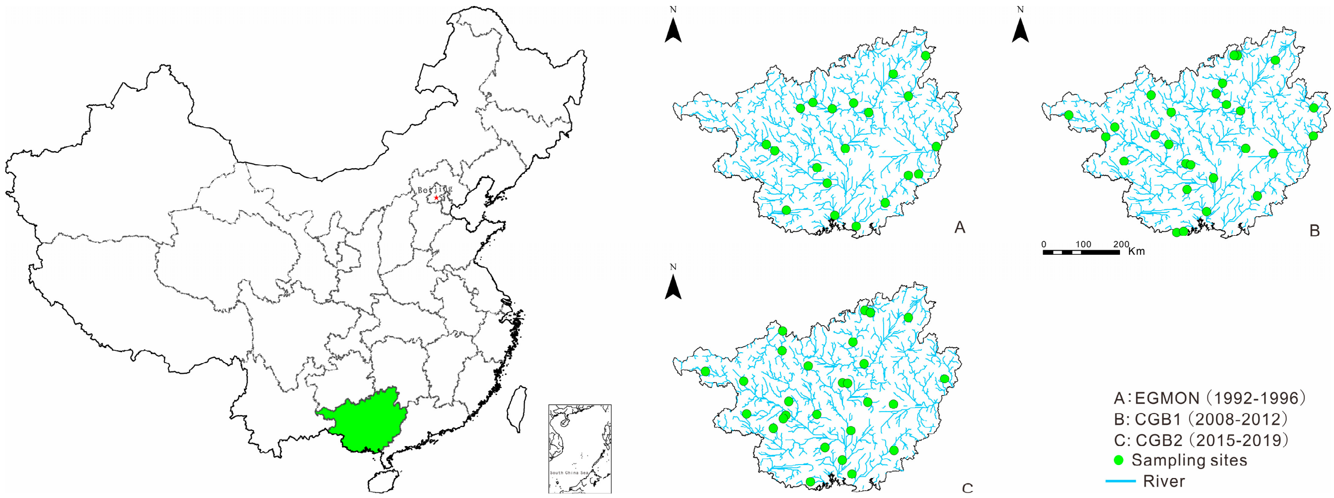

Figure 1. Map showing locations of the study area and samples taken by EGMON, CGB1, and CGB2. EGMON: Environmental Geochemical Monitoring Network Project, CGB: Geochemical Baseline project.

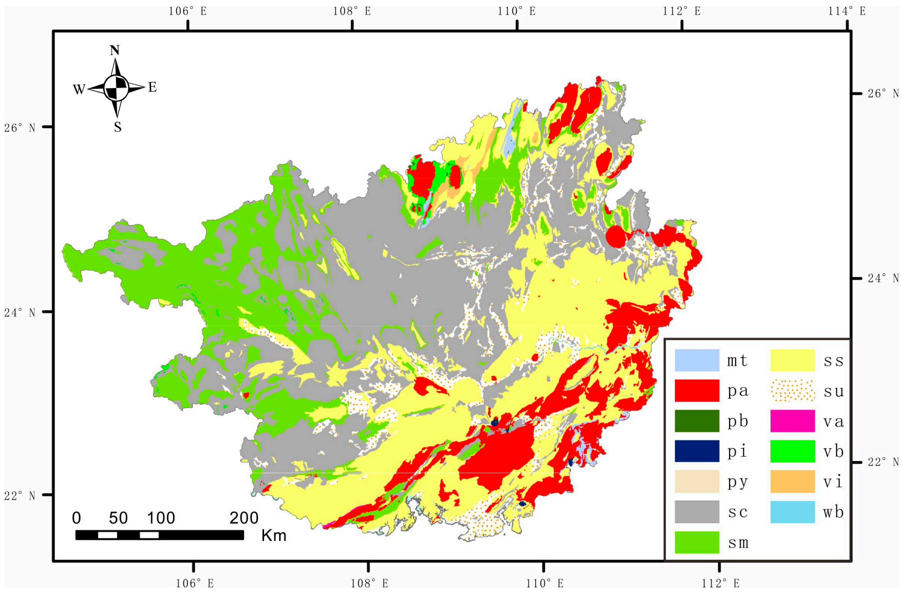

Figure 2. Guangxi geological map. mt: metamorphic rocks, pa: acidic plutonic rocks, pb: basic plutonic rocks, pi: intermediate plutonic rocks, py: pyroclastic, sc: carbonate sedimentary rocks, sm: mixed sedimentary rocks, ss: siliciclastic sedimentary rocks, su: unconsolidated sediment, va: acidic volcanic rocks, vb: basic volcanic rocks, vi: intermediate volcanic rocks, wb: water body.

2.2. Sampling and Analysis Method

2.2.1. Materials and Sampling

In view of recognizing the need for global-scale geochemical baselines that can quantify future human-induced or natural changes in the chemistry of the Earth based on Global Reference Network grid sampling of Earth's surficial materials [30], China initiated the Environmental Geochemical Monitoring Networks (EGMON) project from 1992 to 1996 [14]. Most of the samples were collected in 1995. Samples of Alluvial soil, formed by flood sediments, were collected, and the sampling locations were mostly in the floodplains of large catchment basins ranging from 1000 to 10,000 km^2 [15]. The first China Geochemical Baselines Project (CGB1), as part of the Global Geochemical Baselines Project [30], was conducted from 2008 to 2014 [17], and most samples were collected in 2010–2012. The Second China Geochemical Baselines Project (CGB2) was carried out between 2015 and

2019 [18]. Samples of alluvial soil, formed from drainage sediments, were collected from 3382 and 1741 locations in CGB1 and CGB2, respectively, according to a global reference network grid cell in mainland China (9.6 million km^2). Sample locations were designated at the outlet plains of drainage catchments ranging in area from approximately 1000 to 5000 km^2, with most locations being 2000–3000 km^2 in area. The topsoil samples were collected from the surface to a depth of 25 cm, and the litter was scraped off; the minimum weight of each sample was 2.5 kg.

Temporal changes in heavy metal concentrations may increase or decrease, and a major issue is whether these changes can be detected by soil monitoring. Sampling materials and monitoring sites must indicate that contaminants build quickly enough to be revisited on subsequent occasions [31]. The sample media from the EGMON and CGB were the same; both were alluvial soils formed from catchment sediments (overbank/floodplain/delta sediments) through river transportation (Figure 3). All runoff materials are transported to the same outlet or plain to form soil through drainage network channels (Figure 3). The transported samples collected from the outlets of large drainage catchments are excellent media, representing the natural background and anthropogenic emissions of the area. The contamination of alluvial soils occurs relatively quickly. Pollution comes from diffuse sources, such as natural weathering, mining, industries, residents, pesticides, and fertilizers. Rainfall on land picks up and transports pollutants into watercourses and deposits them in low-reach plains, overbanks, or fluvial terraces.

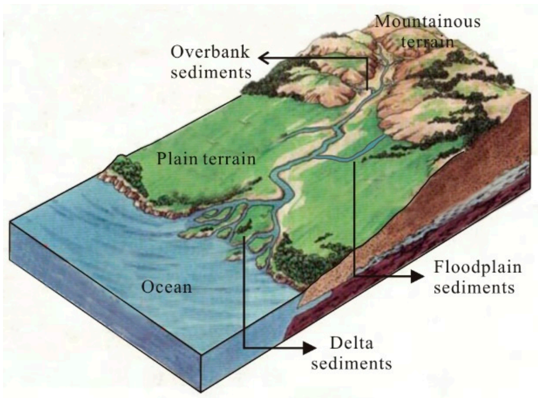

Figure 3. Figure showing the sampling sites.

Twenty samples from the EGMON project and 26 from the CGB1 and CGB2 projects were collected in Guangxi, as shown in Figure 1.

2.2.2. Sample Preparation and Laboratory Analysis

All samples were prepared and subjected to chemical analyses in the same laboratory. The samples were air-dried and homogenized, and each raw sample was split into two sub-samples; one was sieved through a mesh (<2 mm) for laboratory analysis, and the other was stored for future investigation. The sieved sample was ground to <74 μm in an agate mill for laboratory analysis.

An aliquot (0.25 g) was weighed and placed in a test tube, and 10 mL of HF, 5 mL of HNO_3, and 2 mL of $HClO_4$ were added to digest the samples. The test tube was heated in a boiling water bath until it dried. After cooling, 8 mL of 1:1 aqua regia (aqua regia (1 HNO_3 + 3 HCl): pure water = 1:1 vol.) was added to decompose the residue. The solution was diluted with 2% HNO_3 and then analyzed by ICP-MS to determine Cd and Zn. Arsenic was determined by hydride atomic fluorescence spectrometry, and Pb was determined by X-ray fluorescence spectrometry [32]. The detection limits were 1.00 mg/kg, 0.02 mg/kg, 2.00 mg/kg, and 4.00 mg/kg for As, Cd, Pb, and Zn, respectively. The accuracy of the method was assessed by analyzing the soil reference materials (GSS-1, GSS-2, GSS-17, GSS-19, GSS-25, GSS-26, GSS-27) [33] 34 times, and the ΔlgC was less than

0.10 ($\Delta lgC = \mid lgC_i - lgC_s \mid$; C_i is the average of measured values and C_s is the standard reference value).

2.3. Factor Selection

Four anthropogenic factors—land use, the spatial distribution density of major pollution sources, gross domestic product (GDP), and the normalized difference vegetation index (NDVI) in Guangxi—were selected, and the geology background, temperature, precipitation, and digital elevation model (DEM) were selected as natural factors. Geology background and land use were type variables, whereas the others were numeric variables. Gross domestic product, NDVI, and land use were variable factors, and data from 1995, 2010, and 2015 were selected to represent the factor characteristics of the EGMON, CGB1, and CGB2 sampling periods. Data on land use, GDP, NDVI, temperature, and precipitation were collected from the Resource Environmental Science and Data Centre, Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences (https://www.resdc.cn/data.aspx?DATAID=123, accessed on 17 January 2022). Temperature and precipitation data are presented as annual mean values. Digital elevation model data were collected from the Geospatial Data Cloud Website (http://www.gscloud.cn/search, accessed on 26 January, 2021), and major pollution source data for Guangxi were collected from the Guangxi Hechi Ecological Environment Bureau (http://sthjj.hechi.gov.cn/, accessed on 26 January, 2021). The spatial analysis module of ArcGIS 10.4 was used to calculate the nuclear density to obtain the pollution source density of Guangxi. The spatial distributions of the influencing factors in Guangxi Province are shown in Figures 4–7.

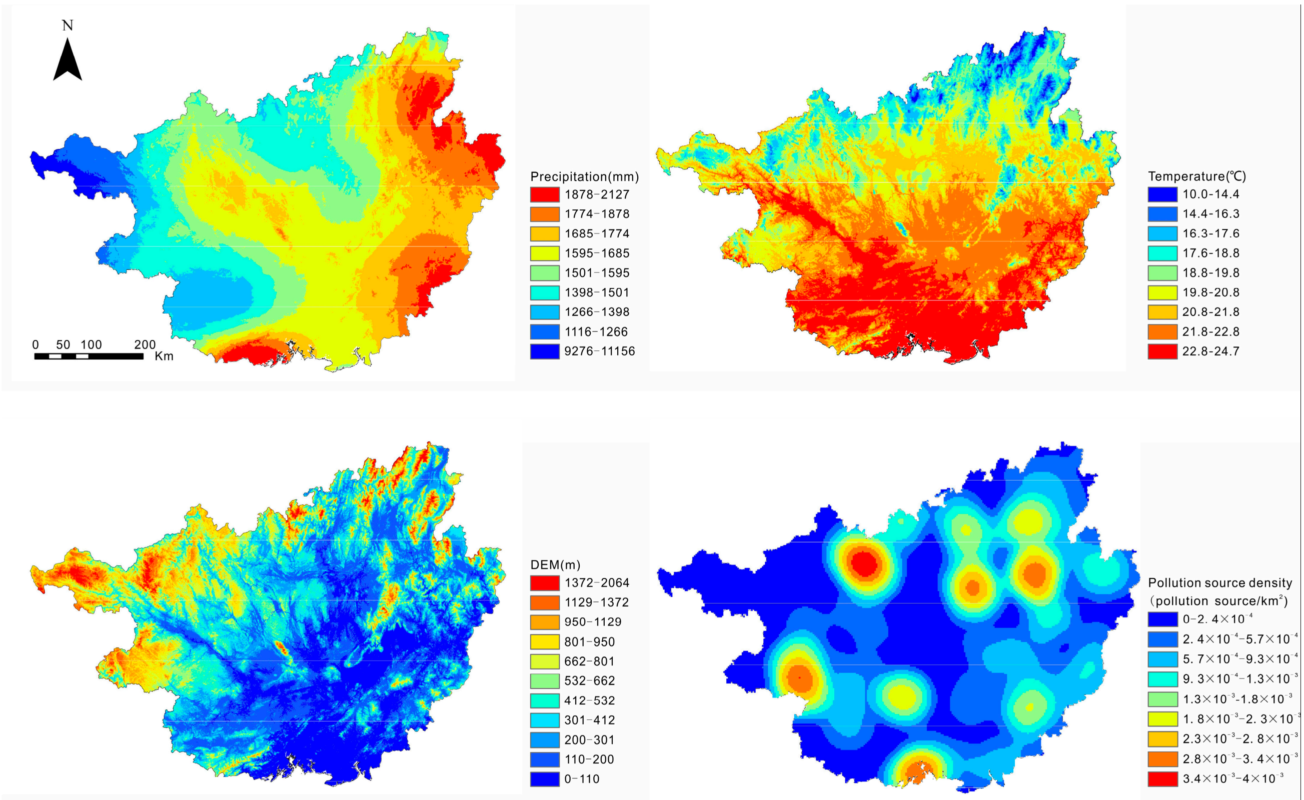

Figure 4. Maps showing influencing factors of Guangxi. DEM: digital elevation model.

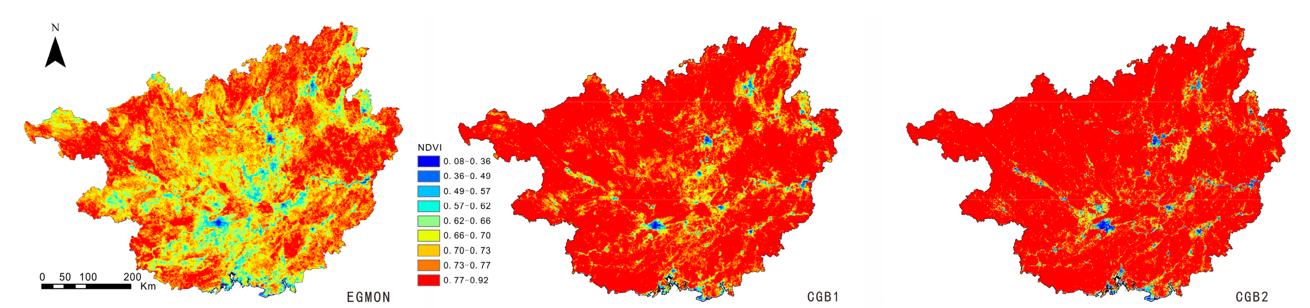

Figure 5. NDVI maps of EGMON, CGB1, and CGB2. NDVI: normalized difference vegetation index.

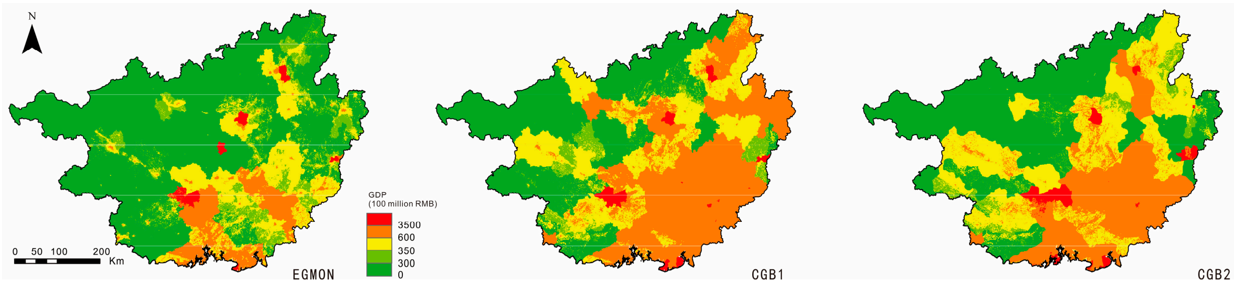

Figure 6. Gross domestic product (GDP) maps of EGMON, CGB1, and CGB2.

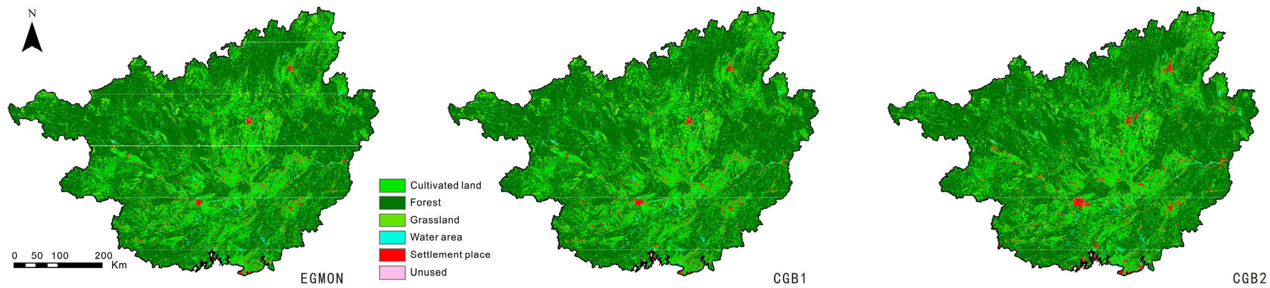

Figure 7. Land use maps of EGMON, CGB1, and CGB2.

2.4. Random Forest Algorithm

Random forest is a classic combined classifier algorithm proposed that was by Breiman [34]. A bagging algorithm was used to generate training sample subsets, and a classification regression tree was used as a meta-classifier, which was randomly selected to split the current node when building a single cart tree. This double random (random training set and random attribute) strategy results in a greater difference between meta-classifiers, which improves the classification performance [35].

Random forest is a combination of tree classifiers $\{h(x,\theta_k), k = 1, \ldots\ldots\}$, and its meta-classifier $h(x,\theta_k)$ is a complete growth and nonpruning classification regression tree. x is the input vector, and $\{\theta_k\}$ is an independent and identically distributed random vector and determines the growth process of a single classification regression tree. For classification, the output of random forest is the result of simple majority voting, and the output is the simple average of the output of a single tree.

Random forest has many advantages; for example, the algorithm can incorporate both continuous and categorical attributes by using the cart algorithm as its meta-learning algorithm. Moreover, the decision tree is of great use in identifying differences and shows better classification performance owing to the combination of the bagging algorithm and randomly selected candidate feature splitting, which prevents overfitting and improves tolerance to noise.

Another prominent feature of random forest is the calculation of the importance of variables. First, the random forest algorithm adds disturbance by the random reordering of a variable of the training samples, and then it observes the change in the classification accuracy of all samples in the decision tree before and after disturbance to measure the variable importance.

Random forest analysis was completed using R3.4.2 [36]. The method used in this study is illustrated in Figure 8.

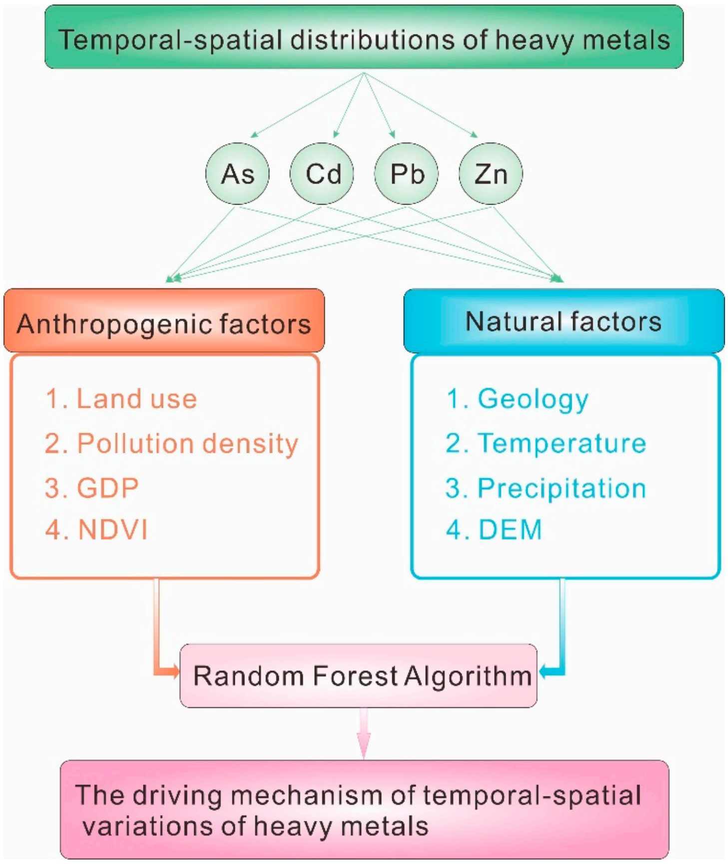

Figure 8. Flow chart showing the classification method used in this study.

3. Results

3.1. Descriptive Statistics

Table 1 shows the statistical parameters of the As, Cd, Pb, and Zn concentrations in the EGMON, CGB1, and CGB2 projects. The maximum values of As, Cd, Pb, and Zn (1270.72 mg/kg, 30.61 mg/kg, 1385.64 mg/kg, and 3724.96 mg/kg respectively) for CGB1 were the highest, indicating that heavy metals were heavily enriched in the CGB1 project. In addition, the coefficients of variation of As, Cd, Pb, and Zn were 405.67, 370, 314.1, and 320.28, respectively, in the CGB1 project, which were also higher than those of the other two projects, suggesting that they had the strongest spatial variations. Moreover, As, Cd, and Pb showed the highest median values (12.58 mg/kg, 0.26 mg/kg, and 31.04 mg/kg, respectively) in the CGB1 project, and Zn showed the highest median value in the CGB2 project. The medians of As, Cd, and Zn were lowest in the EGMON project, and the median of Pb was lowest in CGB2.

Table 1. Descriptive statistics of heavy metals in the EGMON, CGB1, and CGB2 projects.

		As	Cd	Pb	Zn
EGMON	Mean	15.77	0.17	38.35	85.98
	CV	193.49	70.45	72.28	79.51
	Median	7.80	0.13	34.50	72.00
	Min	2.10	0.05	14.00	17.50
	Max	144.00	0.47	137.00	342.00
CGB1	Mean	59.71	1.57	83.06	218.96
	CV	405.67	370.00	314.10	320.28
	Median	12.58	0.26	31.04	79.42
	Min	3.12	0.10	16.10	37.96
	Max	1270.72	30.61	1385.64	3724.96
CGB2	Mean	12.81	0.39	32.35	87.84
	CV	78.07	10	75.50	61.38
	Median	12.17	0.24	26.95	80.22
	Min	2.47	0.03	10.60	27.15
	Max	50.42	1.53	137.92	261.79

Units: mg/kg. CV: coefficient of variation.

3.2. Spatiotemporal Distributions of Heavy Metals

The heavy metal geochemical maps of the three projects (Figure 9) were drawn using the inverse distance weighting method in ArcGIS 10.4 with the European Union soil heavy metal pollution standard values (indicated by the triangular symbol on the color scale) as the thresholds. Arsenic showed the strongest enrichment in the three projects. In the EGMON project, As-anomalous areas were mainly distributed in the east and west of the study area, and the proportion of alluvial soil samples exceeding the limit of 20 mg/kg of As was approximately 10%. As-anomalous areas in the CGB1 project were distributed in the northwest and southeast of the study area, and the proportion exceeding this limit was approximately 23%. In addition, the As-anomalous areas in the CGB2 project were mainly distributed in the northwest and northeast of the study area, showing an exceeding proportion of 11%, and the anomalous intensity and range in the CGB1 project were both weaker than those in the CGB1 project.

In the EGMON project, the Cd content at all sampling sites was below the Cd EU heavy metal pollution threshold of 1000 ug/kg. In the CGB1 project, the Cd-anomalous areas were mainly distributed in the northwest of the study area, with an exceeding proportion of 17%, while the Cd-anomalous intensity and range decreased significantly, showing an exceeding proportion of 7% in the CGB2 project.

The anomalous areas of Pb and Zn in the EGMON project were mainly distributed in the northwest and southeast of the study area, and the proportions of alluvial soil samples exceeding the limits of 70 mg/kg Pb and 160 mg/kg Zn were both approximately 5%. The exceeding proportions of Pb and Zn in the CGB1 project were approximately 17% and 13%, respectively. Compared with the previous two projects, the anomalous intensity and range of Pb in the CGB2 project decreased significantly, with an exceeding proportion of 3.5%, and the anomalous intensity and range of Zn in the CGB2 project were significantly lower than those in the CGB1 project but higher than those in the EGMON project, with an exceeding proportion of 7%.

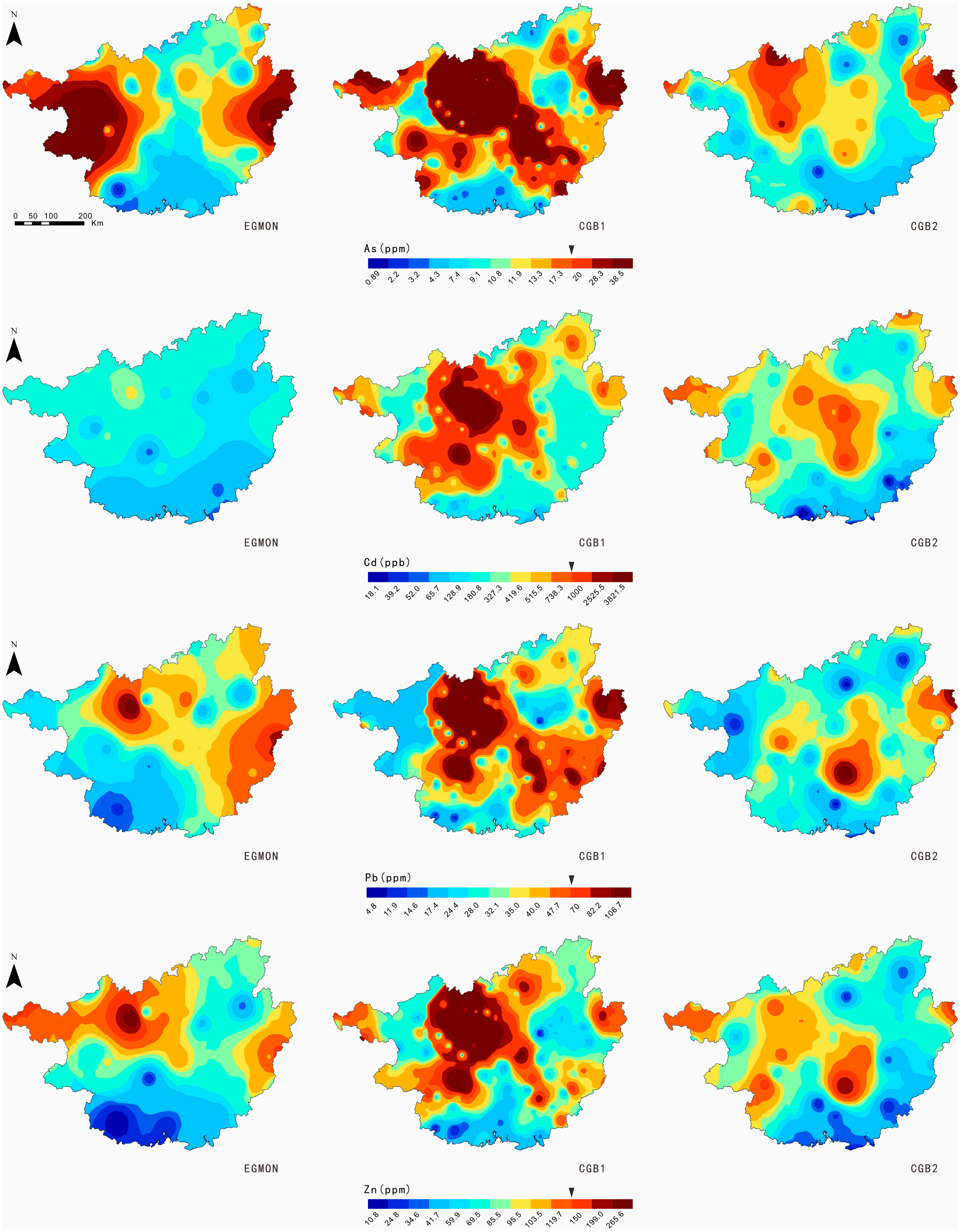

Figure 9. Geochemical maps of As, Cd, Pb, and Zn concentrations in Guangxi. The triangle indicates the threshold of EU heavy metal pollution standard.

4. Discussion

Land use affects soil quality and eco-environmental function, which may be related to soil chemical availability and environmental migration conditions as well as fertilization and irrigation under different land use conditions [37,38]. Gross Domestic Product likely reflects the environmental problems caused by rapid economic development, including industrial and commercial development [39]. The density of the pollution sources around the sampling sites directly reflects the influence of industrial emissions on the heavy metal content of the soils. Pollution can contaminate the downstream soils through atmospheric sedimentation and surface runoff [40,41]. The NDVI is a positive anthropogenic factor that indicates an improved ecological environment and reduced rocky desertification in karst areas [42]. Natural heavy metals in the soil originate from weathering, erosion, and the transport of parent materials. Geological lithology likely reflects the type of parent material. Temperature and precipitation are climatic factors that determine the weathering and denudation rate of parent materials, and lastly, the DEM can determine the path and difficulty of element migration.

The variable importance of the influencing factors, calculated using the random forest algorithm, is illustrated in Figure 10. The spatial variations in As in the EGMON project were mainly affected by precipitation, followed by the spatial distribution density of pollution sources and GDP. The As-anomalous areas geographically coincided with poor-precipitation areas. The greater the rainfall, the stronger the weathering and leaching, while the batholith ions in the soil are more easily lost; thus, the soil is acidic. Fe–Mn concretions are often associated with rich heavy metals because of their poor crystallinity, large surface area [43], high surface negative charge, and the isomorphic substitution of manganese oxides. Fe–Mn concretions in the soil decompose through the acidification process, which leads to the migration of heavy metals from the solid state to the ionic state, resulting in a relatively low heavy metal content in the soil. Natural factors were the key factors regulating the spatial variation of As, with a proportion of more than 60% in the EGMON project. As spatial variation was controlled by GDP and the spatial distribution density of pollution sources in the CGB1 project, the proportion of anthropogenic factor importance was approximately 58%. China experienced rapid economic development during this period, and extensive economic growth has brought many problems, such as the wanton discharge of pollutants and resulting environmental pollution, which were the key factors controlling the spatial distribution of As in the CGB1 project. Arsenic is mainly derived from smelting, pigments, glass, and paper manufacturing in industry, and in agriculture, arsenide is mainly used in pesticides, algicides, and preservatives [44]. The As-anomalous areas were decreased in CGB2 compared with CGB1, and the proportion of anthropogenic factor importance was approximately 55%. The results of the random forest analysis showed that the pollution source was still the key factor affecting the As spatial distribution; however, the NDVI took second place and should be given more focus for the positive role that it plays. The NDVI of the study area increased significantly in the CGB2 project compared with the previous two projects. Vegetation likely regulates surface runoff and conserves soil and water, thereby improving soil quality and the ecological environment. Therefore, it can be concluded that a higher NDVI is associated with a lower degree of rocky desertification; thus, the soil erosion and pollutant contents decreased correspondingly, reflecting the positive impact of human activities on the spatial distributions of heavy metals [45,46].

The key factors regulating the Cd spatial distribution in the EGMON project were natural factors, including DEM, temperature, and geological lithologies, the proportion of which was 61%. The Cd-anomalous areas geographically coincided with low-lying areas; Cd is an active element that migrates more easily than other heavy metals, and low-lying areas can gather materials eroding from the surrounding high-relief areas, resulting in the accumulation of Cd. GDP was the most important factor regulating the spatial distribution of Cd in the CGB1 project, with a proportion of anthropogenic factors of approximately 53%. Cd is a by-product of Zn smelting, which is mainly used in batteries, dyes, and plastic stabilizers, and is more easily absorbed by crops than other heavy metals [47]. The anomalous intensity and range of Cd in CGB2 decreased significantly, with precipitation being the main factor affecting its spatial distribution.

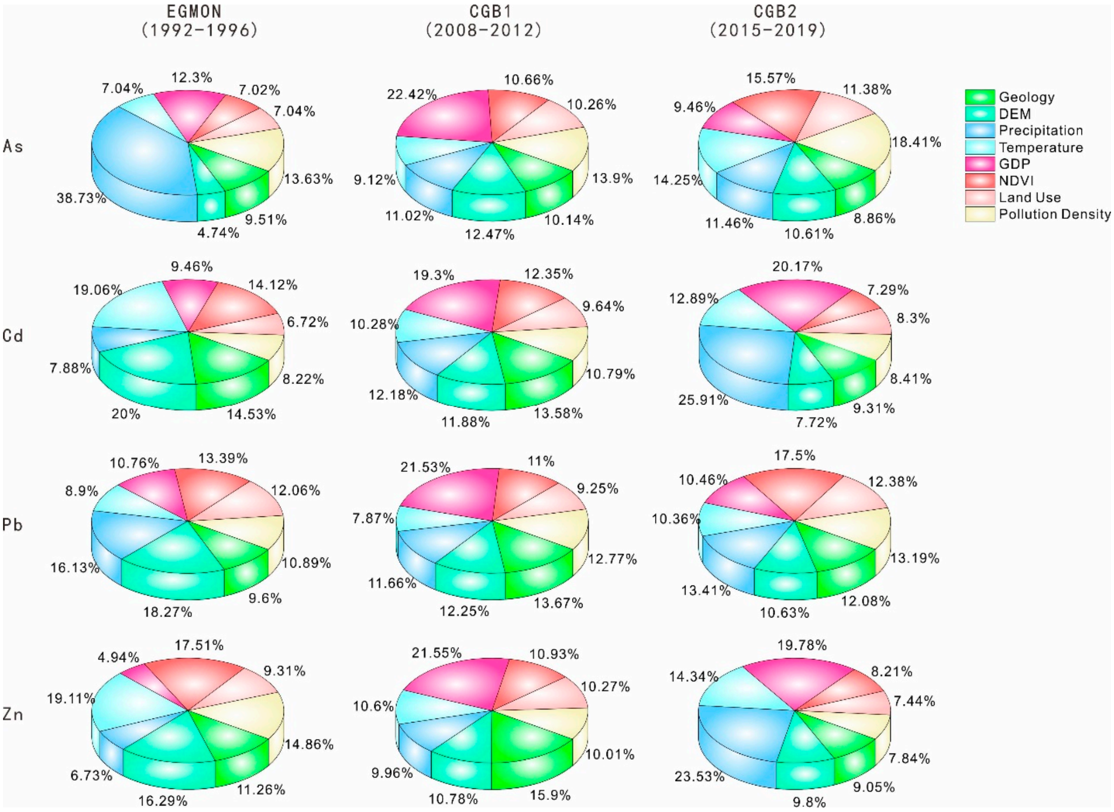

Figure 10. Influencing factors of spatiotemporal distributions of heavy metals.

The spatial variation in Pb in the EGMON project was mainly controlled by the DEM and precipitation, and the proportion of natural factors was approximately 53%. High wet deposition was accompanied by high soil Pb content in Guangxi in the EGMON project, which was different from the other elements. Leaded gasoline was used in China during the EGMON project period; thus, Pb from the exhaust emissions of motor vehicles using leaded gasoline would be adsorbed onto particles and enter the soil through wet deposition [48]. Gross Domestic Product is an important factor controlling the spatial distribution of Pb in the CGB1 project. During this period, leaded gasoline was completely banned in China; thus, lead in soils mainly originated from mining, smelting, leaded coatings, foundry, and other industrial production activities [49]. In the CGB2 project, NDVI was the controlling factor affecting spatial variations in Pb, suggesting a positive role for human activities. The implementation of vegetation restoration and the control of rocky desertification decreased the contributions of upstream rocks; thus, the heavy metal content in the alluvial soils decreased accordingly.

The spatial variation in Zn in the EGMON project was mainly affected by temperature, and the proportion of natural factor importance was approximately 53%. There was a negative correlation between Zn content and temperature. Zn is more active at high temperatures and easily migrates from the solid state to the ionic state, resulting in relatively low Zn content in soils. In the CGB1 project, the GDP was still a key factor, and the proportion of anthropogenic factor importance was greater than 53%. Zn pollution sources include zinc mining, smelting and processing, machinery manufacturing, zinc plating, instrumentation, synthesis, and papermaking. Tire wear and coal combustion also produce zinc and zinc compounds. Precipitation was the most important factor affecting the spatial variation in Zn in the CGB2 project, whereas GDP still played an important role. It was found that the Zn-anomalous areas changed compared with the CGB1 period, which might have been due to the development of the local economy.

In conclusion, the surface soil environmental quality in Guangxi was the best during the EGMON project (1992–1996) period. The disturbance of human activities was relatively small, and the spatial distribution of heavy metals was mainly driven by natural factors. In the CGB1 project period (2008–2012), surface soils showed obvious heavy metal pollution due to rapid economic growth and poor attention to environmental protection. In the CGB2 project (2015–2019), economic growth slowed down, environmental protection was strengthened, the degree of rocky desertification was reduced, and the phenomenon of soil erosion was greatly improved; thus, the anomalous intensity and range of heavy metals decreased compared with that in the CGB1 project.

The factors influencing the spatial distributions of Cd and Zn were similar (Figure 9). Cd is a dispersed element that is closely associated with middle- to low-temperature Pb–Zn deposits and occurs in sphalerite, wurtzite, and other minerals as isomorphisms. Both Cd and Zn are sulfophilic elements with similar ionic radii; therefore, their geochemical behavior is consistent. It is generally accepted that, at the local scale, soil-forming parent materials are among the most important factors affecting heavy metal distribution in soils [50]. However, this study found that wet deposition associated with the DEM is among the most important factors responsible for the spatial distribution of heavy metals in karst areas at a regional scale. The intense tropical rainfall associated with the special geochemical properties of carbonates may be the key factor controlling mass migration and, thus, heavy metal accumulation in karst areas.

Spatial variations in heavy metal concentrations are caused by many factors, including numerical variables (such as GDP and NDVI) and categorical variables (such as geology background and land use). In the past, owing to the limitations of methods, most studies have only focused on numerical variables of the spatial variations of heavy metals, lacking a comprehensive study of both numerical and categorical variables. In this study, numerical and categorical variables were evaluated for the first time using a random forest algorithm. This research promotes an understanding of anthropogenic and natural influences on the spatiotemporal distribution of heavy metals and is of great significance for environmental monitoring and governance. It is of great significance to study the distribution of heavy metals on large spatial and temporal scales, as well as the potential influencing factors. It is necessary to monitor the spatial and temporal changes in heavy metals on a regional scale over long time periods and clarify the impact of human disturbance on natural environmental change, which is also one of the original intentions of long-term geochemical projects in China.

5. Conclusions

In conclusion, the surface alluvial soils showed the strongest heavy metal accumulation in the CGB1 project, followed by the CGB2 and EGMON projects. Arsenic showed the strongest enrichment among the three projects. Natural factors were among the most important factors affecting the spatial distribution of heavy metals in the EGMON project, particularly precipitation for As, DEM for Cd and Pb, and temperature for Zn. Gross Domestic Product was a key factor regulating the spatial distribution of all heavy metals in CGB1. The NDVI and precipitation were important factors controlling heavy metal variations in CGB2. As a positive anthropogenic factor, the NDVI improved the degree of rocky desertification, reduced the heavy metal contents of As and Pb, and promoted the decomposition of oxides and hydroxides and thus the migration of Cd and Zn.

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