Mapping and Modeling Heavy Metal Concentration in Soil

Based on multi-spectral images and environmental variables

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Abstract

Heavy metal contamination of soil is becoming a serious issue in the Anthropocene and a major concern for landscape remediation projects. Remote sensing provides a new opportunity to detect the heavy metal distribution in soil more efficiently.

Using Camden County, Burlington County and Atlantic County in New Jersey as a study area, this study integrates geochemical data derived from soil survey samples, with Landsat 7, Landsat 8 imagery, and environmental factors to build a model to estimate the distribution of As, Pb, and Cu in topsoil and identify the high-risk areas of heavy metal contamination. The relationships between the three heavy metals and soil environmental factors were investigated using linear regression model and with the proposed method, the heavy metal distributions were estimated in three years 2002, 2017 and 2021. From the spatial distribution maps of the three metals concentrations, there are findings that high concentrations of the three types of heavy metals all occur around the agricultural and suburban areas.

1 Introduction

Heavy metal contamination has been an anthropogenic environmental issue contributed by human disturbance including industrial, agricultural activities, which also poses health threat to human body. Compared to the air and water, soil is less monitored and traditional soil sample survey is labor-consuming and limited in sample location. However, remote sensing provides a new opportunity to model and detect the heavy metal concentration in soil over time with the help of geographic and environmental attributes.

This study is to build a heavy metal model using multi-spectral satellite images, environmental variables and previous soil sample data to detect the spatial concentration of three types of heavy metal, As, Cu, Pb.

2 Literature review

In the past 15 years, there are much research to explore the potential of using remote sensing and spectral indices to model and map heavy metals in topsoil. Melendez-Pastor et al. studied and proved the significant role of remote sensing in soil toxic metals detection. Especially the reflectance spectral information of minerals in soils (clay mineral ratio) could be used to detect heavy metals (Wu, YZ; Malley, D.F.; Ben-Dor, E.). Choe et al.'s research showed significant correlations between Pb, Zn, Cu and As and different spectral absorption features (e.g., peak depth, area, asymmetry and band ratio). Peng et al. (Digital Mapping of Toxic Metals in Qatari Soils Using Remote Sensing and Ancillary Data) proposed the use of Landsat 8 imagery from January or February to extract spectral indices (including band2-7, BCI, NDVI, Brightness, TVI), in combination with auxiliary data like proximity to road to build a model using Cubist tool for estimating the heavy metal concentrations in soils. They mainly focus on arsenic (As), chromium (Cr), nickel (Ni), copper (Cu), lead (Pb) and zinc (Zn), among which Cu works best. Liu used Sentinel-2A multispectral imagery to investigate the stress exerted by heavy metals in soils on crops. Yun Yang et al. (Estimating the heavy metal concentrations in topsoil in the Daxigou mining area, China, using multispectral satellite imagery) used Landsat 8 Imagery with elevation to estimate Cu, Pb, and As concentrations in topsoil via the proposed GA–BP model. They find significant correlations between the concentrations of Cu and B2, B3, B4, CMR, MNDWI, Greenness, EVI, and NDVI, and between Pb and B2, B3, and B4, EVI and brightness factors. FarhadMirzaei et al. (Modeling the distribution of heavy metals in lands irrigated by wastewater using satellite images of Sentinel-2) applied Sentinel-2 satellite (band 2-12) to model the concentration of Pb, Cu, and Ni using linear regression, multivariate, and step-b.

To summarize, the season of the landsat images is important in detecting the soil conditions, Peng's paper finds the winter (January and February) landsat images perform better than summer, consider there will be less vegetation canopy cover and more soil exposed to be detected.
Another takeaway is that these studies mainly focus on metals Pb, Zn, Cu, As, Ni, Cr, which prove to have significant correlations with multi-spectral satellite images and that could be a potential metal range to study; similarly, the spectral indices these researchers use would be a great reference for this study, which are listes in the following dataset chapter 3.2.2.

3 Study area and data source

3.1 Study area

The study area is located east of Delaware River in New Jersey adjacent to city of Philadelphia, covering Camden county, Burlington county and part of the Atlantic county. The study area covers some suburban areas in its northwest and has 'Pine Barrens' area in the south, which is the largest body of open space on the Mid-Atlantic seaboard between Richmond and Boston with numerous state parks and forests, wetlands. The predominant trees there are pines, oaks, cedars blueberries, cranberries and other acid-loving plants.

In this case, the study area is ecologically significant and has a large amount of pervious soil surface for detection. Meanwhile, a certain amount of agricultural lands and waste management, industrial or military facilities pose threat to the soil in the study area. And sufficient soil sample data conducted by NJDEP previously also provide more opportunity for research.

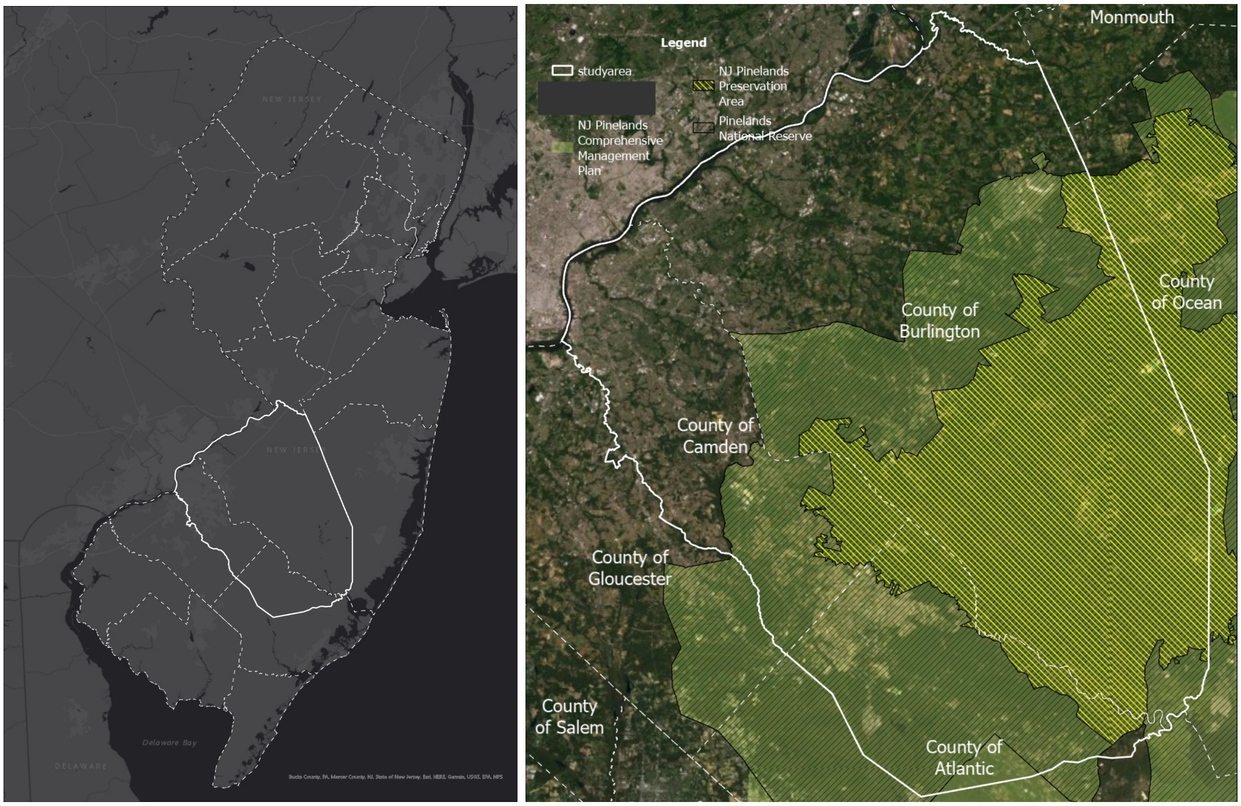


Fig 1a. Study area in New Jersey; 1b. Study area with Pinelands preservation area

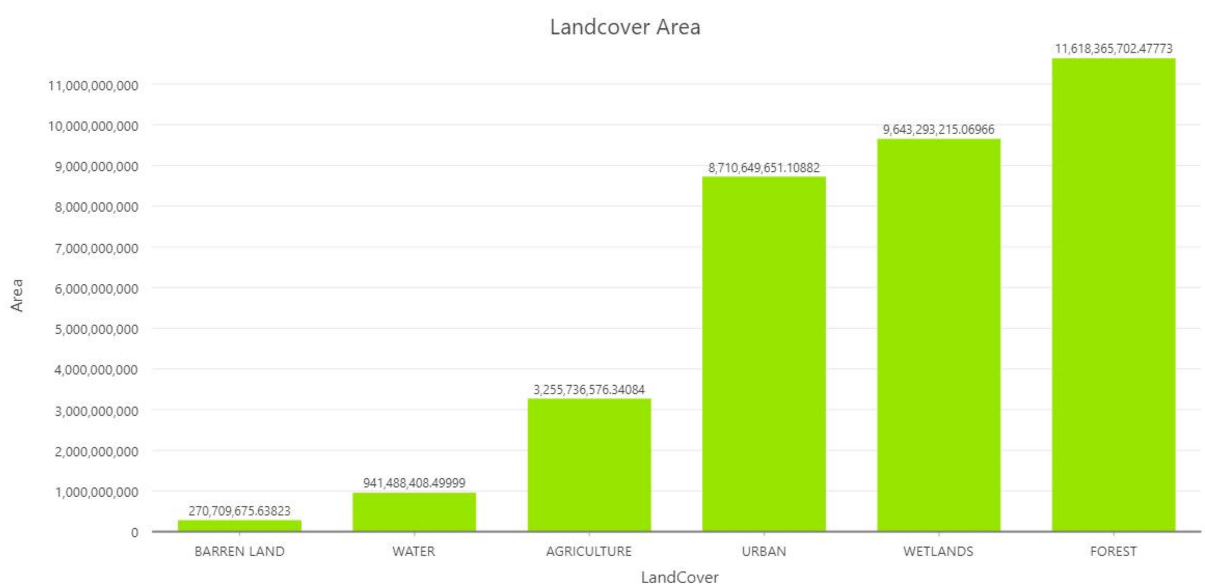


Fig 2. Landcover types and areas in study area

3.2 Dataset

The study is to use two types of data for model building and validation. The first part is the soil sample data from the soil sample survey conducted in 2001 and 2016. Responding to that is the variable data in corresponding years, including the Landsat satellite images in 2001 and 2016 and other environment variables.

	2001 (Model Building)	**2016** (Model Building)	**2022** (for spatial visualization)
Soil Sample Survey Data (80% for training, 20% for testing)	1.NJDEP: characterization of ambient levels of selected metals and cpahs in new jersey soil	2.Site Remediation and Waste Management Program (SRWMP), PAH data	
Land cover (to identify pervious surface)	3.NLCD 2000(National Land Cover Database)	NLCD 2015(National Land Cover Database)	NLCD 2021(National Land Cover Database)
Elevation, Slope, Aspect	Same DEM Data		
Distance to disturbance	Road data, Waste Management facilities data, Military facilities data, brownfield density		
Satellite images (11 bands and multi-spectral images)	5. USGS (Landsat 8) 2002-02	USGS (Landsat 8) 2017-02	USGS (Landsat 8) 2021-02
Heavy Metal Spatial Concentration	Spatial concentration of **Arsenic, Lead, Copper**		

Table 1. Dataset used in the study

3.2.1 Soil sample data

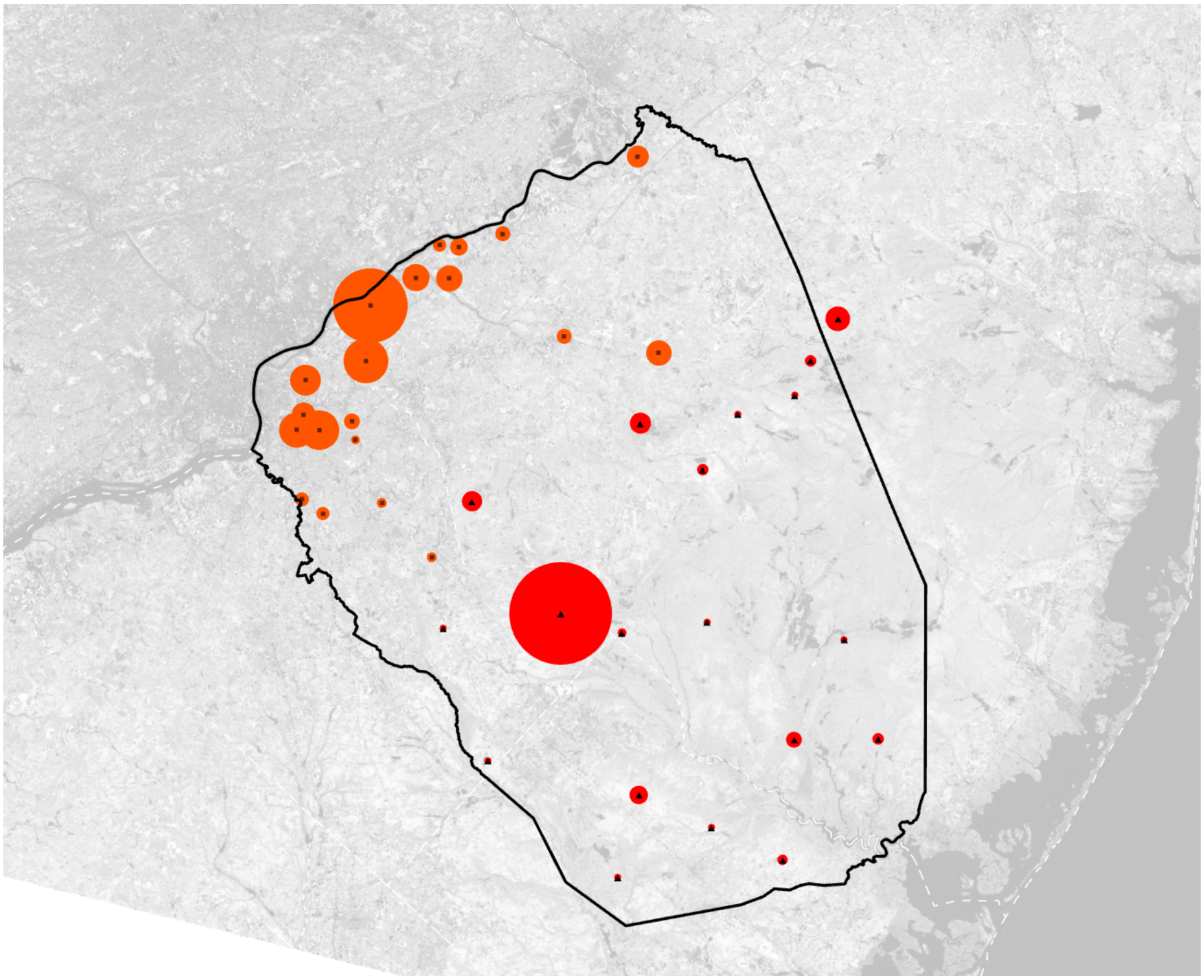


Fig 3. Soil survey sample points (red: 2001 survey sample locations; orange: 2016 survey sample locations; Point sizes represent Lead amount as an example)

This study is to use two sets of soil survey sample data for moel training (Table 2,3): one survey conducted by NJDEP (New Jersey Department of Environmental Protection) in 2001 covered 20 sample locations in the study area, each of which has the measured amount (ppm) of 23 metals; the other survey conducted by SRWMP (Site Remediation and Waste Management Program) in 2016 covered 19 sample locations in the study area, each of which is measured in both shallow and deep soil layer and they each have the measured amount of 22 metals.

These metal sample data could be used for regression analysis to determine the most related variables and help the calibration and validation of the metal distribution model.

SUMMARY OF COASTAL PLAIN RURAL SOIL DATA										
	Sample ID:	NJDEP NRDC Cleanup Criteria	NJDEP RDC Cleanup Criteria	**CP-64**	**CP-65**	**CP-66**	**CP-67**	**CP-68**	**CP-69**	**CP-70A**
Analyte	Date:	03-May-1999	03-May-1999	09-Jun-2001	09-Jun-2001	09-Jun-2001	09-Jun-2001	09-Jun-2001	30-Nov-2000	30-Nov-2000
Metals										
Silver		4100	110	0.18 U	0.19 U	0.20 U	0.19 U	0.18 U	0.079 U	0.093 U
Aluminum		NA	NA	1620	4230	4390	1620	5900	5250	9560
Arsenic		20	20	0.59 B	3.0	2.4	1.1 B	1.5	4.1	8.2
Barium		47000	700	6.0 B	16.8 B	14.9 B	6.7 B	7.8 B	0.14 U	43.1
Beryllium		2	2	0.056 U	0.19 B	0.083 B	0.060 U	0.057 B	0.023 U	0.027 U
Calcium		NA	NA	60.4 B	70.4 B	106 B	65.3 B	59.4 B	3.6 U	4.3 U
Cadmium		100	39	0.068 U	0.071 U	0.077 U	0.072 U	0.066 U	0.034 U	0.040 U
Cobalt		NA	NA	0.48 B	2.2 B	0.91 B	0.47 B	0.61 B	0.057 U	0.067 U
Chromium		NA	120000	2.8	5.7	5.0	2.6	4.9	5.4	12.4
Copper		600	600	3.5	4.1	4.0	2.6 B	3.4	10.1	15.2 J
Iron		NA	NA	1790	4970	3810	1860	3120	4760	11700
Mercury		270	14	0.047	0.044	0.061	0.033 B	0.053	0.10 J	0.31 J
Potassium		NA	NA	71.7 B	135 B	228 B	127 B	130 B	3.8 U	4.4 U
Magnesium		NA	NA	94.4 B	250 B	324 B	126 B	224 B	1.3 U	943
Manganese		NA	NA	12.2 J	252 J	18.4 J	11.2 J	10.6 J	14.6 J	171 J
Sodium		NA	NA	66.3 B	65.6 B	75.8 B	51 B	76 B	9.8 U	12 U
Nickel		2400	250	0.81 B	2.6 B	2.5 B	0.92 B	2.2 B	0.15 U	8.1
Lead		600	400	13.9	20.6	18	16.2	14.1	36.6	250
Antimony		340	14	0.34 U L	0.35 U L	0.41 BL	0.36 U L	0.33 U L	0.19 U L	0.23 U L
Selenium		3100	63	0.39 U	0.41 U	0.45 U	0.42 U	0.38 U	1.1	0.41 U
Thallium		2	2	0.71 U	0.74 U	0.81 U	0.76 U	0.69 U	0.41 U	0.48 U
Vanadium		7100	370	8.0	11.1	13.7	8.1	12.8	20.8	22.5
Zinc		1500	1500	3.8	9.3	9.2	3.9	6.4	11.6	44

Table 2. 2001 soil survey data sample (extracted from: https://www.nj.gov/dep/dsr/publications/Characterization%20of%20Ambient%20Levels%20of%20Selected%20Metals%20and%20cPAHs%20in%20NJ%20Soils_Year%20Three_Highlands,%20Valley%20and%20Ridge,%20and%20Coastal%20Plain%20_Full%20Report.pdf)

Sample ID	Municipality	County	Population Density (2010)	Distance to nearest KCSL (ft)	Area Type	Soil Type	Sample Depth	Aluminum	Antimony	Arsenic	Barium	Beryllium	Cadmium
CAMD01	OAKLYN BORO	CAMDEN	5769	658	Open	Urban land	shallow	8670	1.70	8.4	69.5	0.46	0.630
CAMD02	BERLIN BORO	CAMDEN	2102	1468	Open	Mullica sandy loam	shallow	3360	0.00	1.6	6.7	0.00	0.072
CAMD03	CHERRY HILL TWP	CAMDEN	2939	1780	Open	Fluvaquents	shallow	3520	0.89	8.4	11.3	0.41	0.120
CAMD06	GLOUCESTER TWP	CAMDEN	2776	4560	Open	Tinton sand	shallow	1970	0.39	7.4	10.2	0.12	0.000
CAMD07	HADDON TWP	CAMDEN	5215	1903	Open	Freehold-Downer-Urban land complex	shallow	8140	1.20	13.6	79.5	0.62	0.710
CAMD07	HADDON TWP	CAMDEN	5215	1903	Open	Freehold-Downer-Urban land complex	shallow	9000	1.60	17.3	79.6	0.68	0.640
CAMD07	HADDON TWP	CAMDEN	5215	1903	Open	Freehold-Downer-Urban land complex	shallow	6050	1.30	8.7	74.4	0.52	0.950
CAMD08	VOORHEES TWP	CAMDEN	2507	3269	Forested	Buddtown-Deptford fine sandy loams	shallow	6720	0.00	5.8	22.9	0.38	0.160
CAMD11	CAMDEN CITY	CAMDEN	7394	3040	Open	Urban land	shallow	3800	1.60	6.3	56.6	0.36	0.260
CAMD12	COLLINGSWOOD BORO	CAMDEN	7216	938	Open	Urban land	shallow	4040	1.90	5.2	30.0	0.24	0.096
CAMD13	HADDONFIELD BORO	CAMDEN	4082	2067	Forested	Freehold-Downer-Urban land complex	shallow	2500	0.32	5.4	15.9	0.31	0.150
CAMD14	RUNNEMEDE BORO	CAMDEN	4032	2652	Forested	Freehold-Downer-Urban land complex	shallow	4560	0.71	6.0	19.5	0.26	0.240

Table 3. 2016 soil survey data sample (report see: https://www.nj.gov/dep/dsr/health/statistics-metals-soil.pdf)

For the 2016 soil survey sample data, this study will only use the shallow soil metal data for model building. However, by comparing the shallow and deep data for certain metals (Table 4), it helps to decide the three metals to focus on: Arsenic, Copper and Lead, the metal concentrations of which were significantly higher in shallow soil samples. That would help to detect metals in topsoil using remote sensing.

Arsenic	296	1	Intercept	1.57	0.11	13.89	0.000	*
			Distance	0.00	0.00	-3.81	0.000	*
			Open Area	0.16	0.09	1.72	0.085	
			Density	0.00	0.00	2.66	0.008	*
			Shallow	0.35	0.09	4.00	0.000	*
Copper	296	0	Intercept	2.28	0.14	16.69	0.000	*
			Distance	0.00	0.00	-4.82	0.000	*
			Open Area	0.09	0.11	0.83	0.405	
			Density	0.00	0.00	4.52	0.000	*
			Shallow	0.55	0.11	5.23	0.000	*
Lead	296	0	Intercept	3.16	0.14	22.58	0.000	*
			Distance	0.00	0.00	-5.56	0.000	*
			Open Area	0.22	0.12	1.93	0.053	
			Density	0.00	0.00	4.55	0.000	*
			Shallow	1.18	0.11	10.93	0.000	*

Table 4. Amount of As, Cu, Pb in shallow and deep soil in 2016 soil survey

The following figures (Fig 4a-c) show the histograms of Arsenic, Lead, and Copper in the sample data. The amounts of three metals in the sample locations are all within the NJDEP residential soil cleanup criteria.

To give a summary of these heavy metals' attributes:

Arsenic is a naturally occurring element in the environment that can enter the food supply through soil, water or air from agricultural and industrial sources. The soil cleanup criteria for As is 20 ppm.

Copper is usually found in nature in association with sulfur. Soils naturally contain copper, ranging from 2 to 100 parts per million (ppm) and high accumulation above 600 ppm might come from certain planting activities in agriculture and affects food safety and security.

Lead is a toxic metal that could be emitted into the environment from industrial sources and contaminated sites, such as former lead smelters. A soil lead hazard is defined as bare soil on residential real property that contains total lead equal to or exceeding 400 parts per million (ppm).

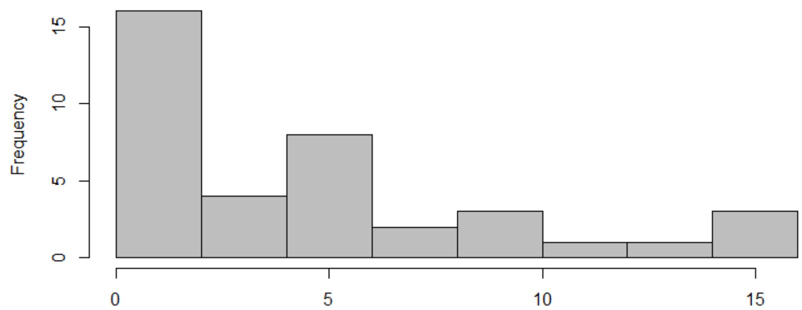


Fig 4a. Histogram of the Arsenic amount in soil samples

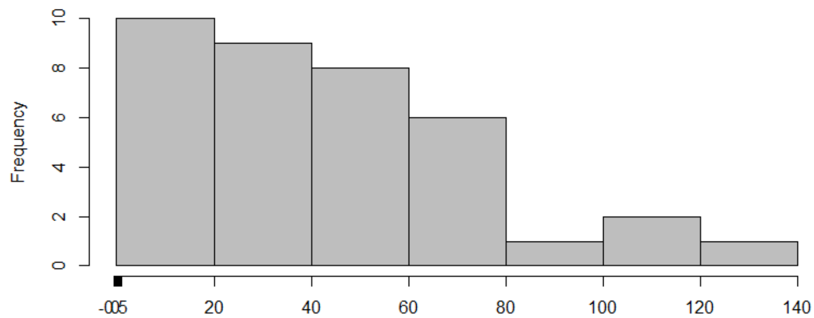


Fig 4b. Histogram of the Lead amount in soil samples

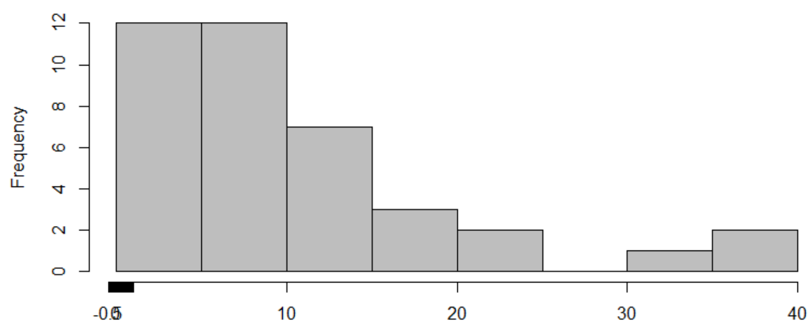


Fig 4c. Histogram of the Copper amount in soil samples

3.2.2 Spectral factors

According to previous studies, soils contaminated by heavy metals display spectral characteristics that differ from those of uncontaminated soils. So for model building, it is significant for this study to consider the spectral factors including both spectral reflectance factors with basic bands and spectral indices related to soil characteristics.

According to the soil sample survey conducted in 2001 and 2016, this study is going to use Landsat satellite images in 2002 Feb and 2017 Feb for reflectance value extraction and model construction, and also use Landsat images in 2021 for the visualization. The following matrices show the 6 bands for each satellite image.

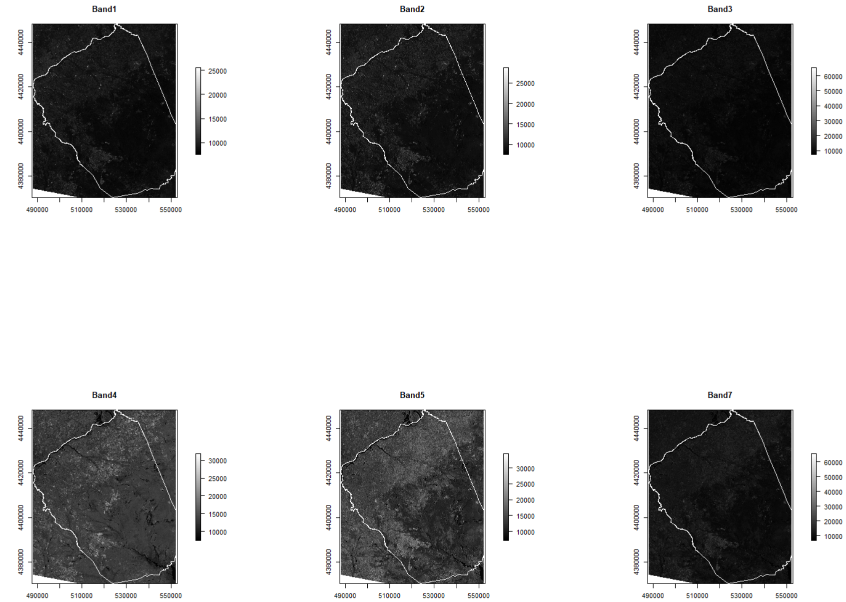


Fig 5a. Landsat 7 Band 1-7 (2002 Feb)

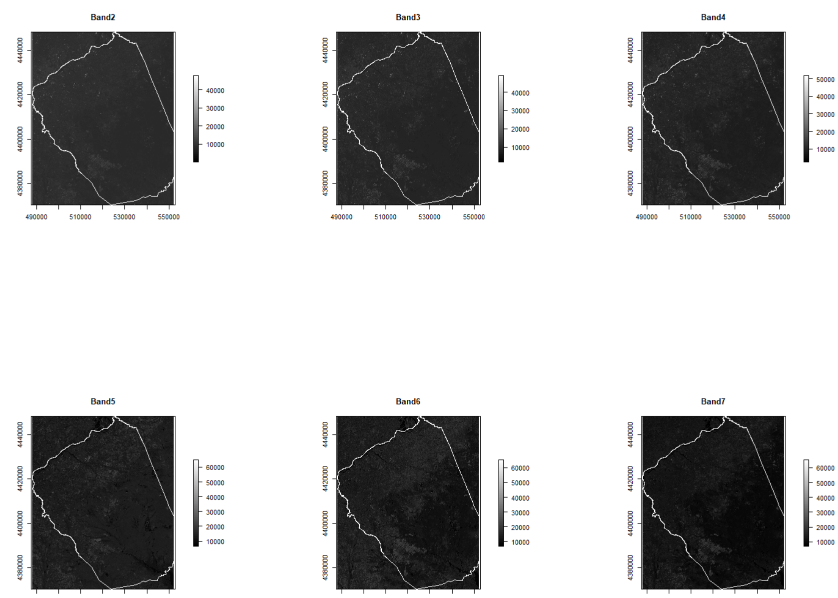


Fig 5b. Landsat 8 Band 2-7 (2017 Feb

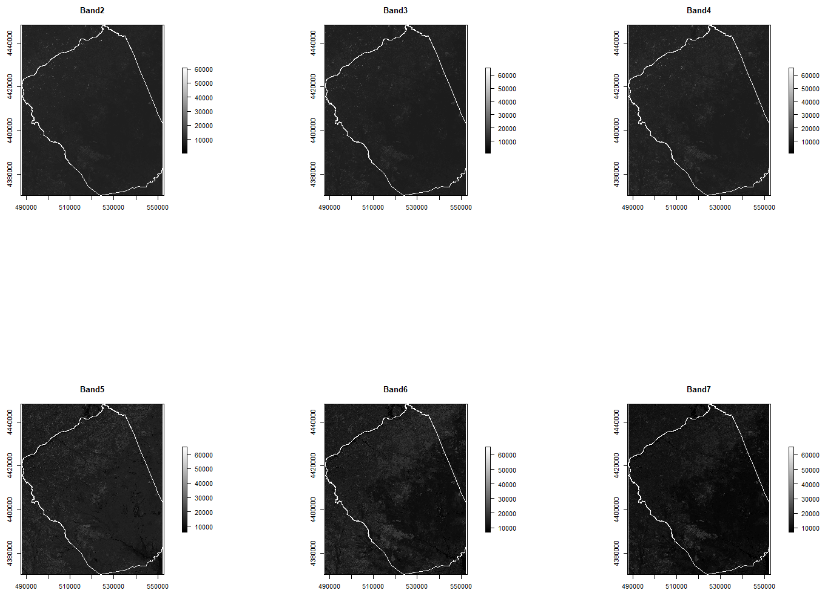


Fig 5c. Landsat 8 Band 2-7 (2021 Feb)

However, sometimes the basic bands won't have a strong connection with the metal distribution. According to the previous studies, these concentrations can also be obtained indirectly from the adsorption or occurrence relationships between the soil water content, clay mineral content, etc.

Consequently, six spectral indices reflecting the soil properties associated with heavy metals were derived from the spectral values of the six bands of the Landsat 7 and Landsat 8 images, and these are presented in Table 5.
The indices related to vegetation health like normalised vegetation index (NDVI) and enhanced vegetation index (EVI) could indirectly represent different soil type and heavy metal concentrations. In addition, the greenness, brightness, and humidity components generated by the tasselled cap transformation could be used to represent the vegetation and soil information. And according to the other studies, the clay mineral ratio (CMR) is related to the clay mineral content of the soil, and can indirectly affect the distribution of heavy metals in the soils. The improved normalised water index (MNDWI) reflects the estimation of the soil water content.

Types	**Factors**	**Definition**
Bands	Band 2 - Band 7	
Multi-spectral Indices	NDVI (normalized differential vegetation index)	(B5-B4)/(B5+B4)

	MNDWI (improved normalised water index)	(B3−B6)/(B3+B6)
	EVI (enhanced vegetation index)	2.5×(B5−B4)/(B5+6×B4−7.5×B2+1)
	Greenness	−0.294×B2−0.243×B3−0.542×B4+0.728×B5+0.071×B6−0.161×B7
	Brightness	0.3561xB2 + 0.3904xB4 + 0.6966xB5 +0.2286xB6 + 0.1596xB7
	CMR (clay mineral ratio)	B6/B7

Table 5. Spectral indices used for assessment of the concentrations of Cu, Pb, and As in the soils (based on Literature review)

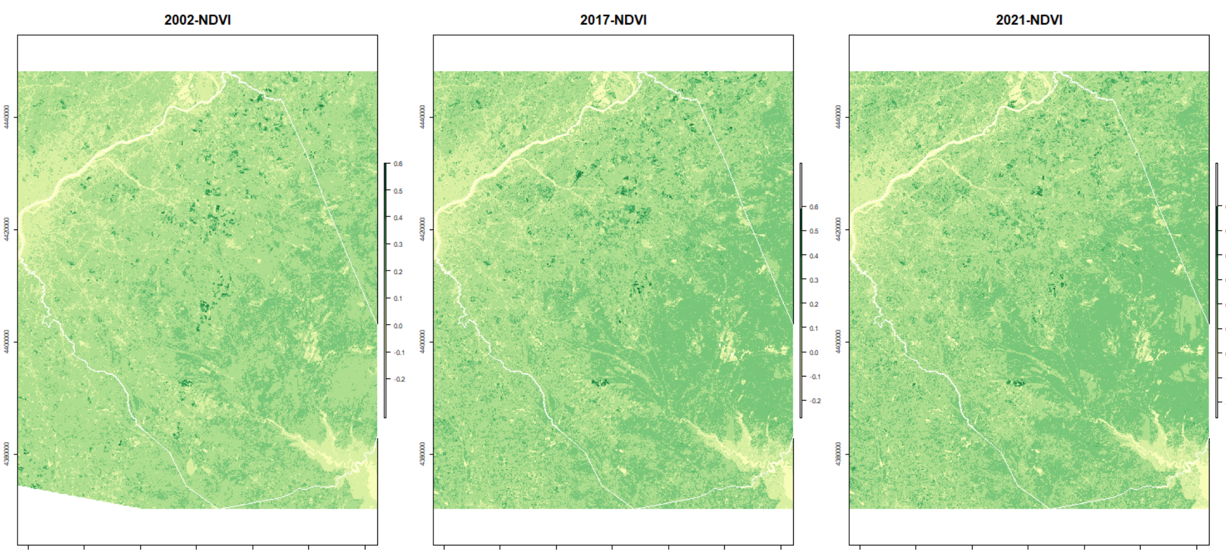


Fig 5a. Spectral Indices NDVI in 2002, 2017, 2021

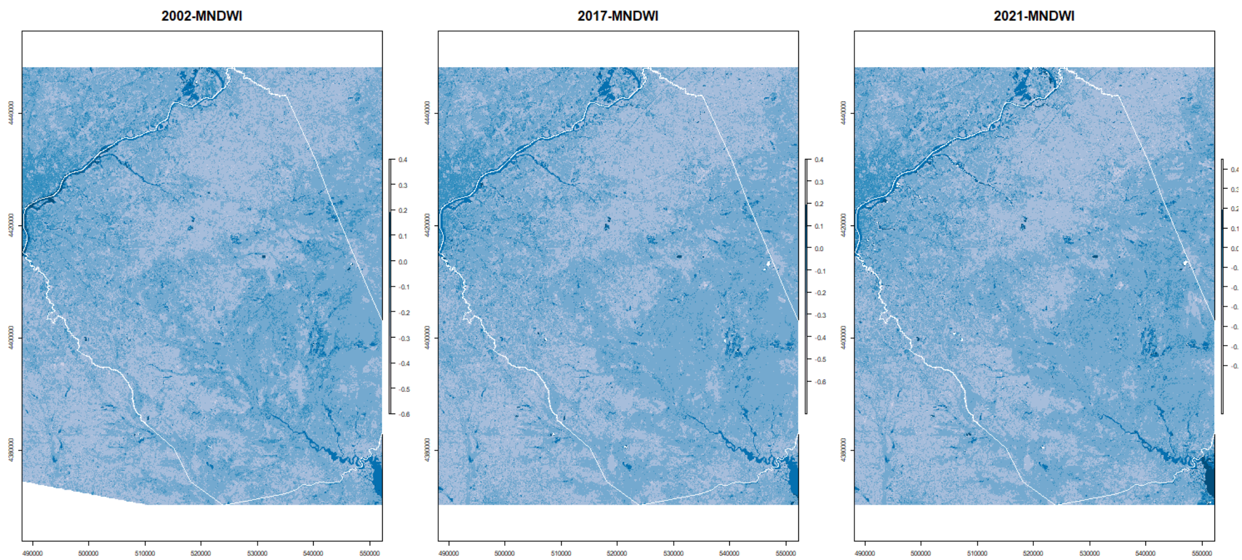


Fig 5b. Spectral Indices MNDWI in 2002, 2017, 2021

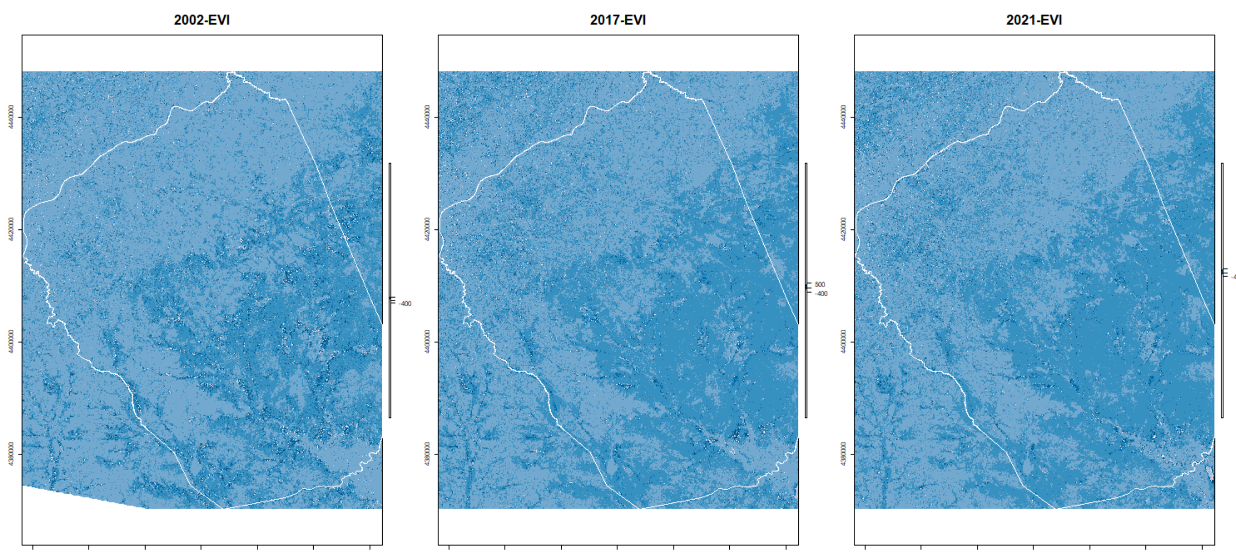


Fig 5c. Spectral Indices EVI in 2002, 2017, 2021

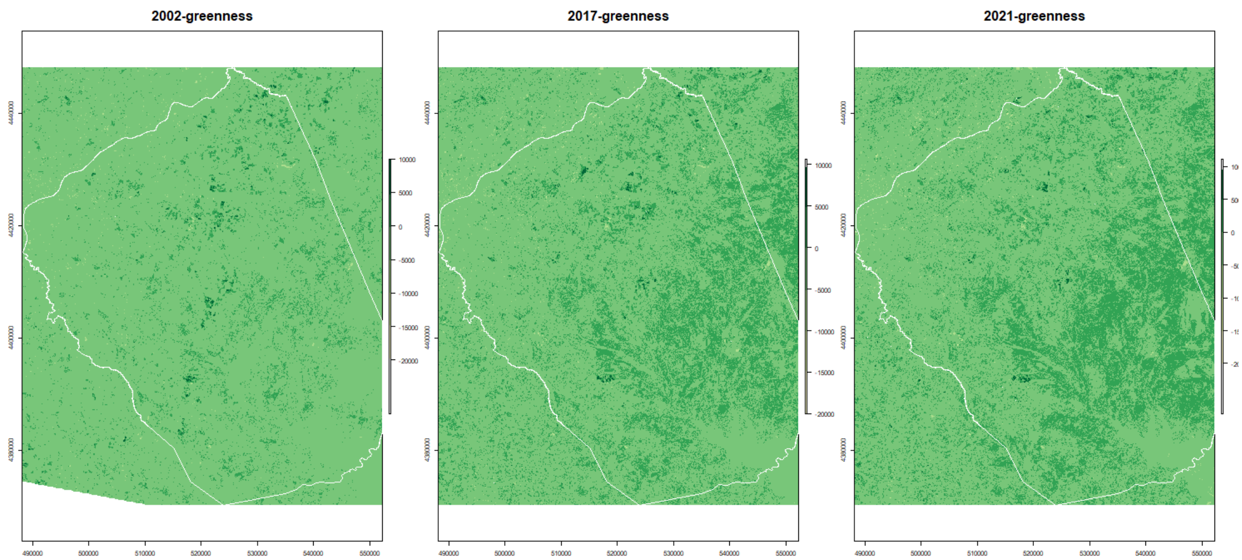


Fig 5d. Spectral Indices Greenness in 2002, 2017, 2021

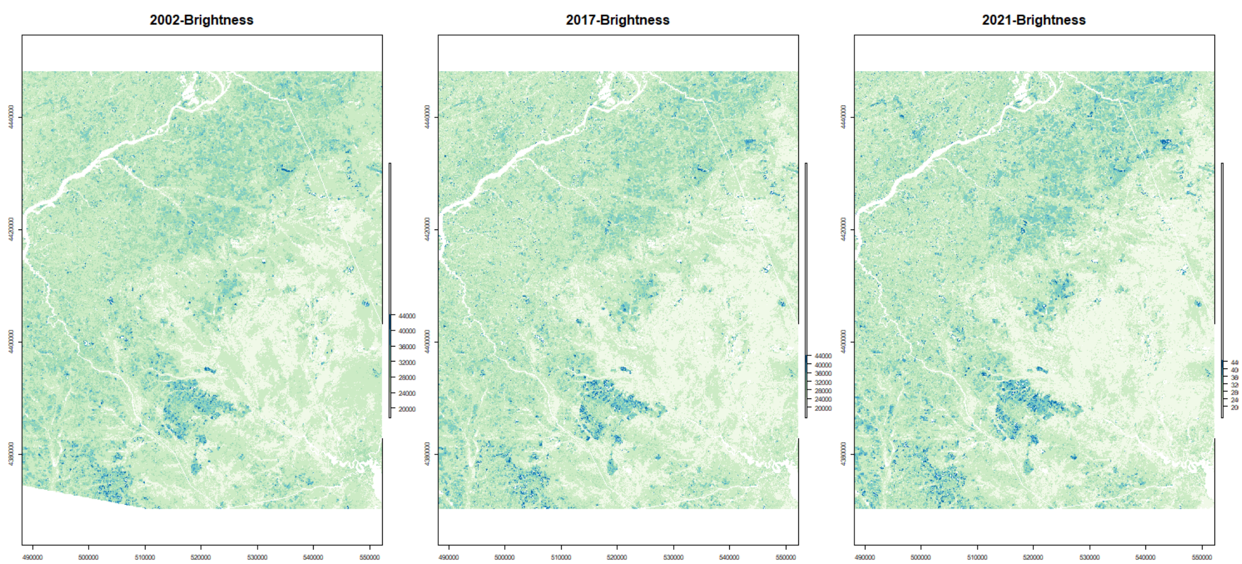


Fig 5e. Spectral Indices Brightness in 2002, 2017, 2021

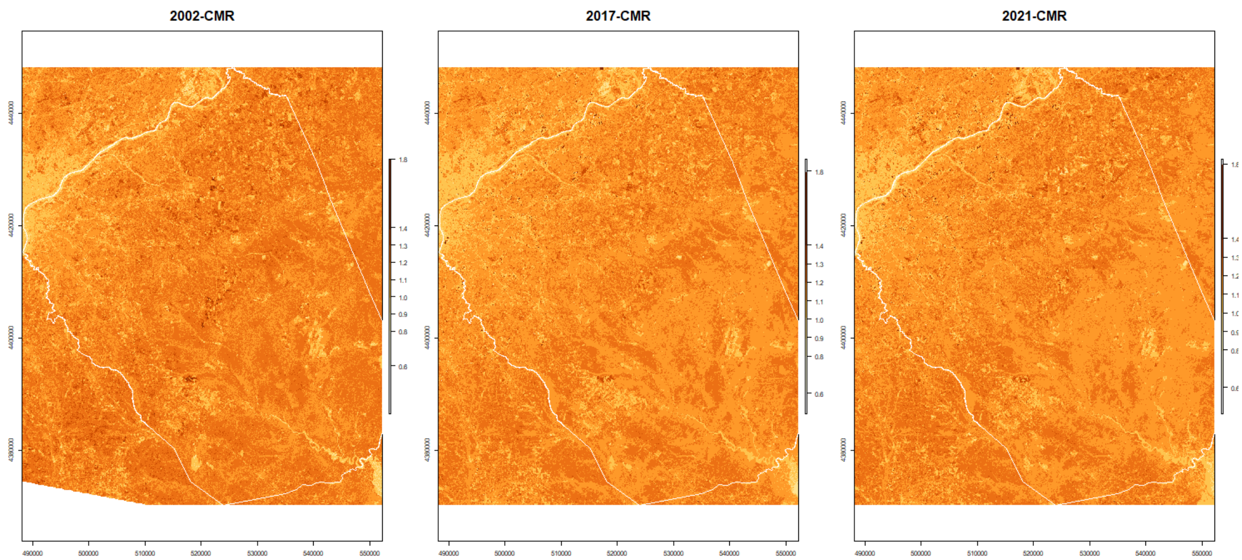


Fig 5f. Spectral Indices CMR in 2002, 2017, 2021

3.2.3 Environmental factors

Besides the spectral factors extracted from remote sensing, environmental factors are also considered in this metal distribution model. The first is the geographic factors including elevation and slope, which could probably affect the movement of heavy metals in terrains. The other is the anthropogenic factors related to human activities, including the distance to road network, waste management facilities and other brownfields, which are shown in the following maps.

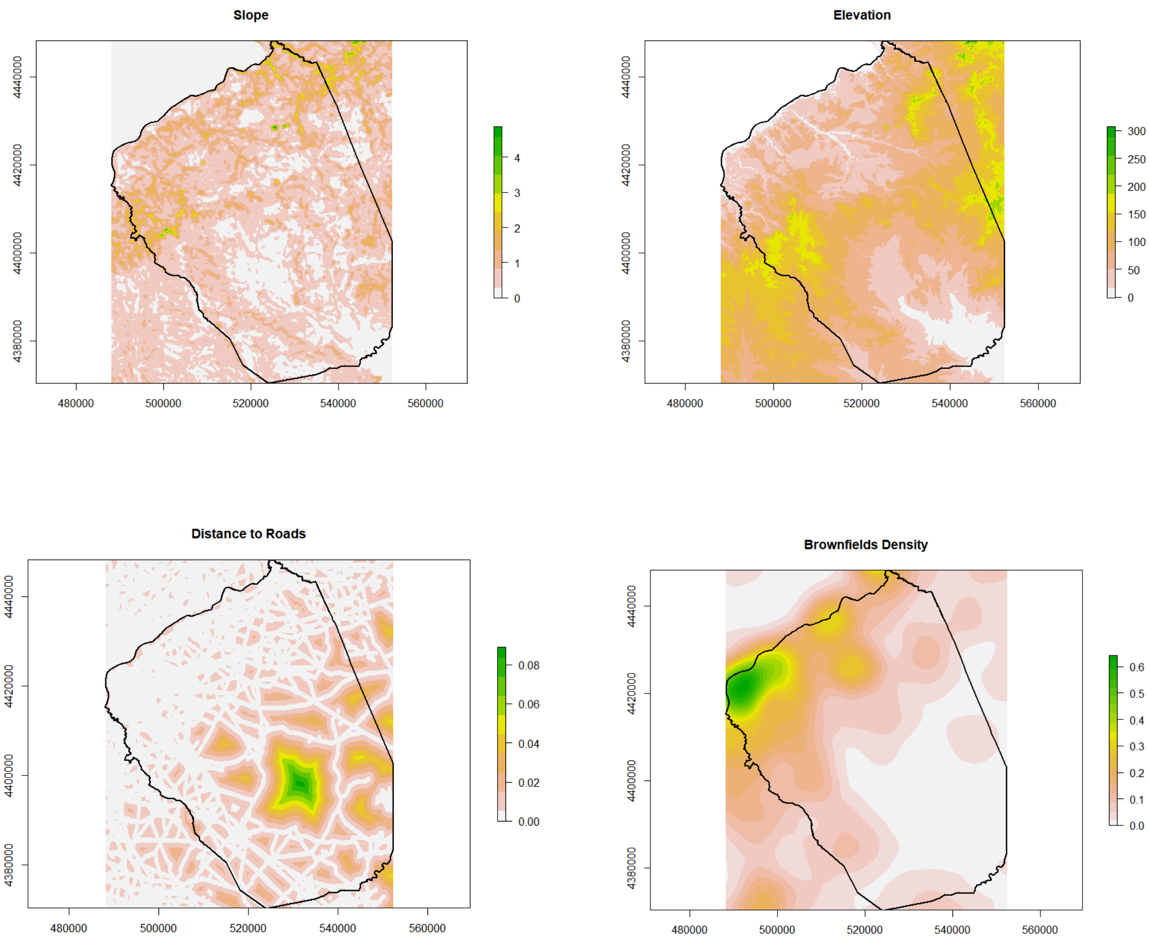


Fig 6a, 6b, 6c, 6d. Environmental factors for heavy metal distribution model include slope, elevation, distance to roads and brownfield density

4 Methodology

4.1 Regression model

Based on the soil sample data and all the potential spectral and environmental factors, the training dataset is prepared by extracting the values of spectral and environmental factors at the 39 sample locations and randomly selecting 80%.

The correlations between the concentrations of the three heavy metals and six spectral bands, six spectral indices and five environmental factors based on linear regression are presented in Table to show the most correlated factors for each heavy metal distribution.

Metals	Arsenic	Lead	Copper
Correlated Factors	Band 2 **	Brownfield Density ***	CMR *
	Brownfield Density **	Band 2 ***	Distance to Military Sites *
	Band 7 **	Band 3 **	Brownfield Density *
	Band 3 **	CMR **	Band 2 *
	DEM *	DEM **	DEM *
	Brightness *	Band 7 *	Band 3 *
	Band 4 *	Brightness *	Band 4 *
	CMR *	Band 5 *	

Table 6. Correlated factors for the three heavy metals

In Table 6, * represents the significance level at $P < 0.05$, while ** denotes the significance level at $P < 0.01$.

The results in Table 6 reveal relatively significant correlations between the concentrations of As and the spectral reflectance values of the B2, B7, B3 and the value of Brownfield density.

The Pb concentrations are significantly correlated with brownfield density, B2, and also B3, B7, CMR, elevation.

The concentrations of Cu display less significant correlations with spectral and environmental factors like CMR, distance to military facilities and B2, B3, B4 probably because of the low copper concentration in this study area.

Therefore, the correlated spectral bands and spectral indices in Table 6 were employed as parameters for the distribution model estimating the Cu, Pb, and As contents of soils in the area.

4.2 Prediction test

The rest 20% of the dataset is then used to test the accuracy of the models of Cu, Pb, and As contents in soil. Based on the following figures of prediction distribution, RMSE and MRE, the Pb model shows higher accuracy and the Cu model works not that well.

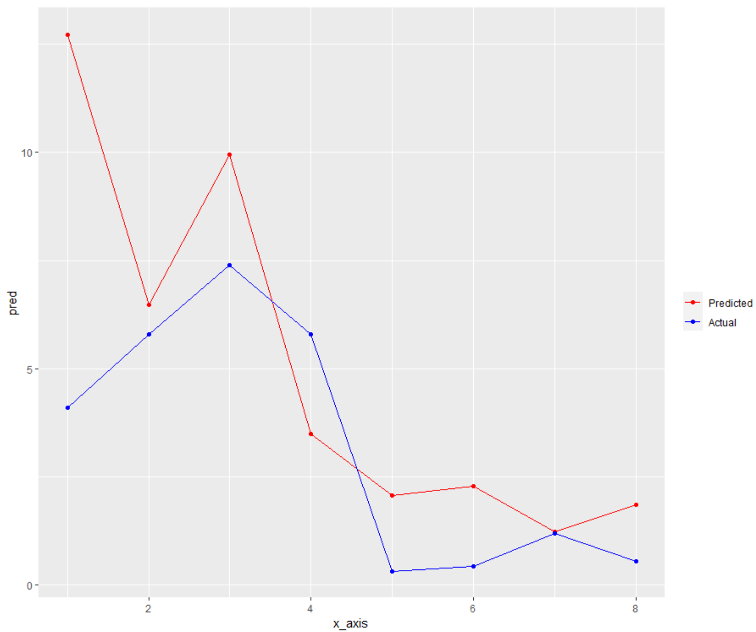


Fig 7a

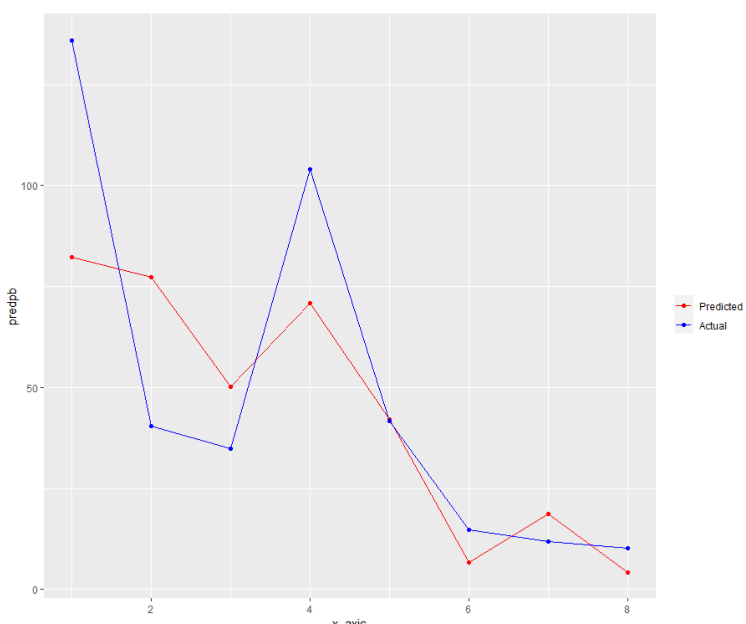


Fig 7b

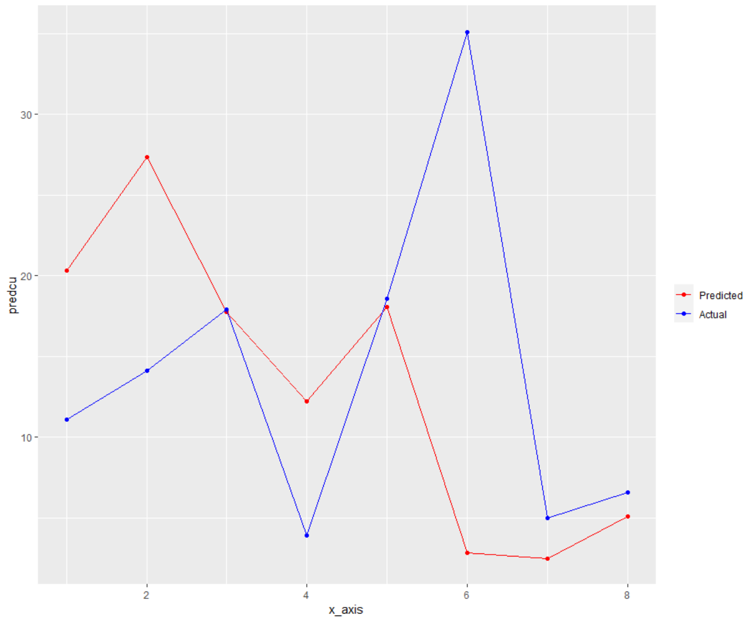


Fig 7c

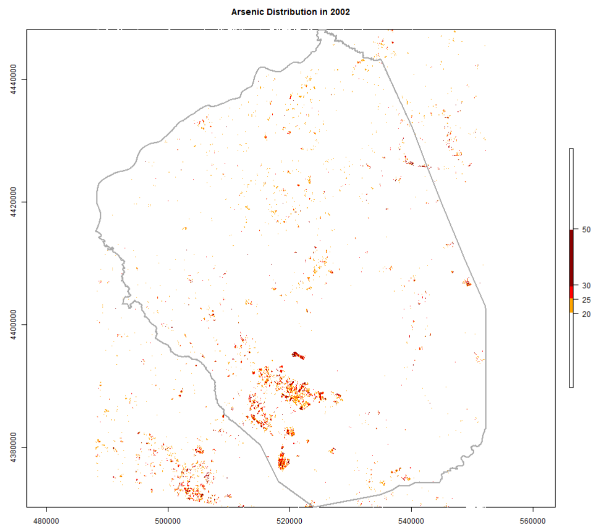
Fig 7a, 7b, 7c. Prediction distributions of (a) As (b) Pb and (c) Cu based on the models

5 Results

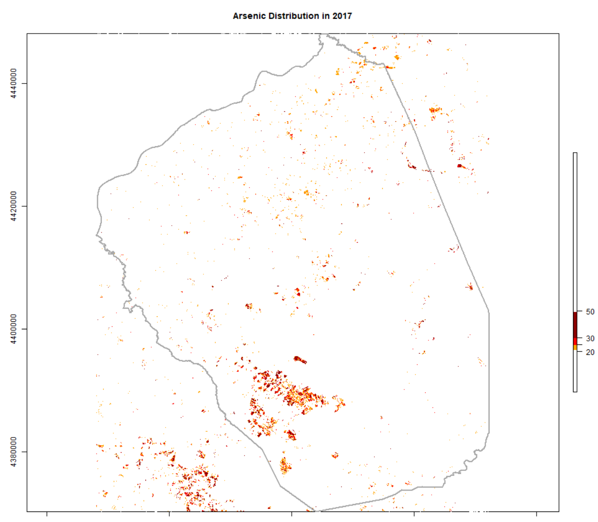
Considering the models are trained based on the sample points on the pervious soil surface, this study uses the pervious surface as a mask to filter the results of the heavy metal distribution in soil.
The spatial distributions of the three heavy metals in soils in the study area based on the models are displayed in Fig 8-10.

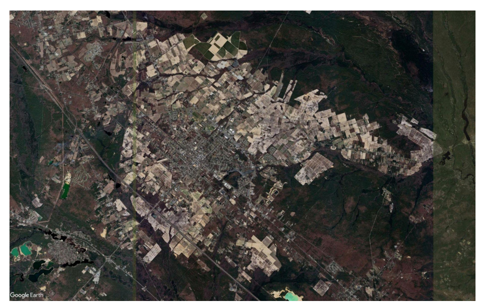
5.1 Arsenic Distribution

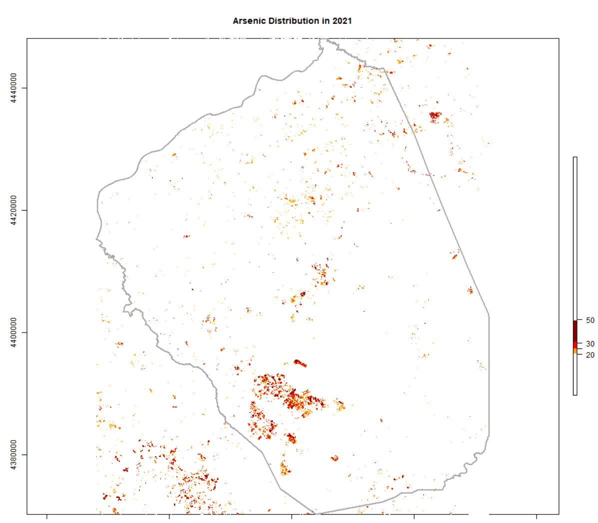
Among the three heavy metals, Arsenic is the only one that exceeds the soil cleanup criteria (20 ppm) in certain places in the study area. The maps in 2002, 2017, and 2021 (Fig 8 a-c) visualize the As distribution that exceeds the 20 ppm criteria. It is apparent that As mainly accumulates around southwest areas, the agricultural lands, which are shown in the following satellite images Fig 8d-f.


Arsenic Distribution in 2002
4440000
4420000
4400000
4380000
480000
500000
520000
540000
560000
50
30
25
20


Google Earth


Arsenic Distribution in 2017
4440000
4420000
4400000
4380000
480000
500000
520000
540000
560000
50
30
20


Google Earth


Arsenic Distribution in 2021
4440000
4420000
4400000
4380000
480000
500000
520000
540000
560000
50
30
20


Google Earth

Fig 8a,b,c. Arsenic distribution prediction in the study area in 2002 (a), 2017 (b) and 2021 (c); Fig 8d,e,f. Satellite images of high concentration areas for Arsenic in 2002, 2017, 2021.

5.2 Lead Distribution

The range of predicted Lead amount in the soil is within the cleanup criteria (400 ppm). They mainly concentrate on suburban and agricultural areas. Zoom in to the high concentration area in the southwest as shown in the previous satellite images (Fig 8d, 8e, 8f), the construction of a large turf farm might contribute most to the Lead accumulation.
By calculating the Lead distribution change from 2002 to 2021, the map (Fig 9d) shows a significant increase.

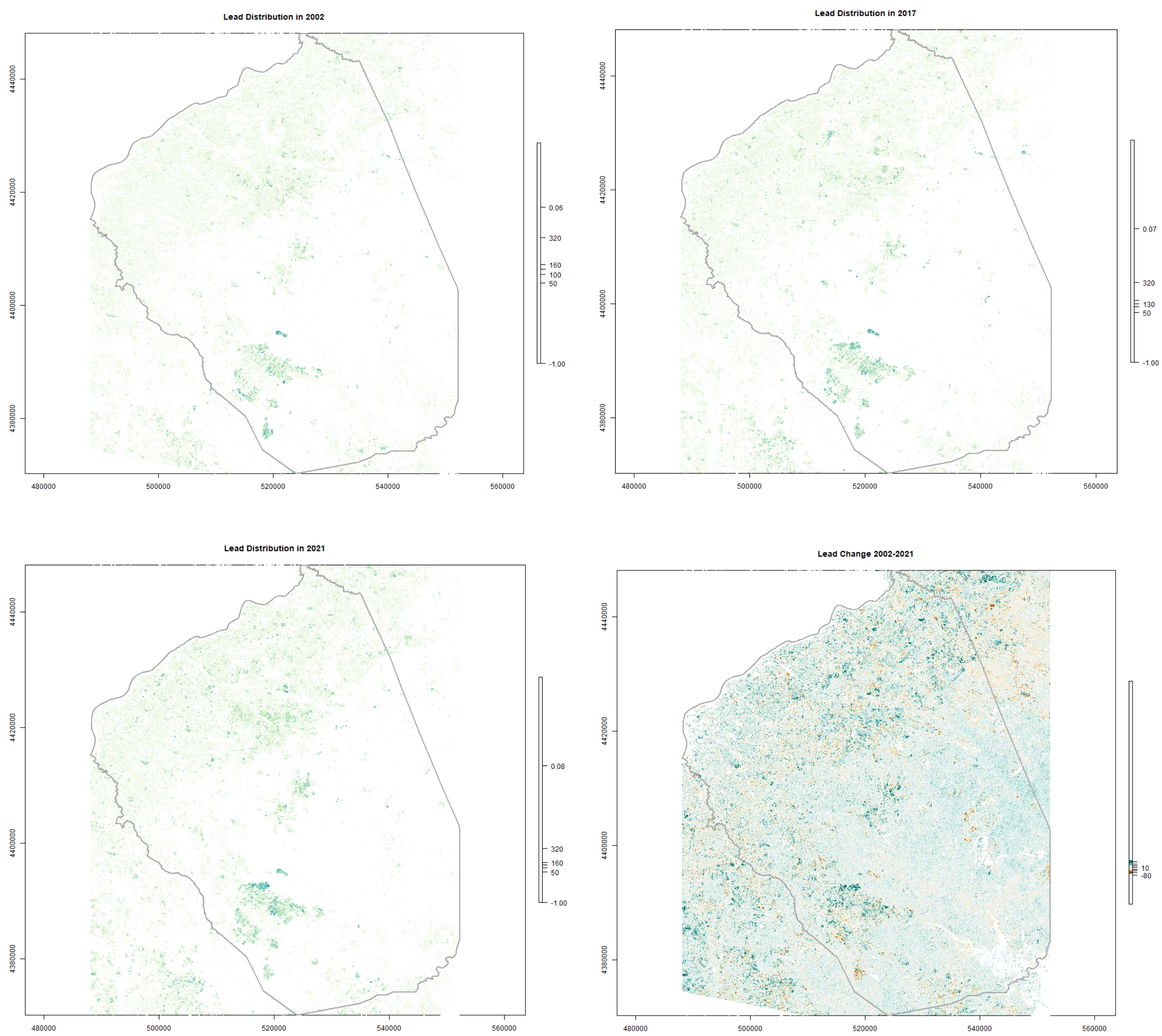


Fig 9a-c. Lead distribution prediction in the study area in 2002 (a), 2017 (b) and 2021 (c); Fig 9d. Lead distribution change from 2002 to 2021

5.3 Copper Distribution

Copper amount in soil is also within the cleanup criteria (600 ppm). Similar to Lead and Arsenic, copper is mainly concentrated in suburban and agricultural areas. The map of copper distribution change from 2002 to 2021 shows a decrease in copper concentration in urban areas and a slight increase in agricultural lands.

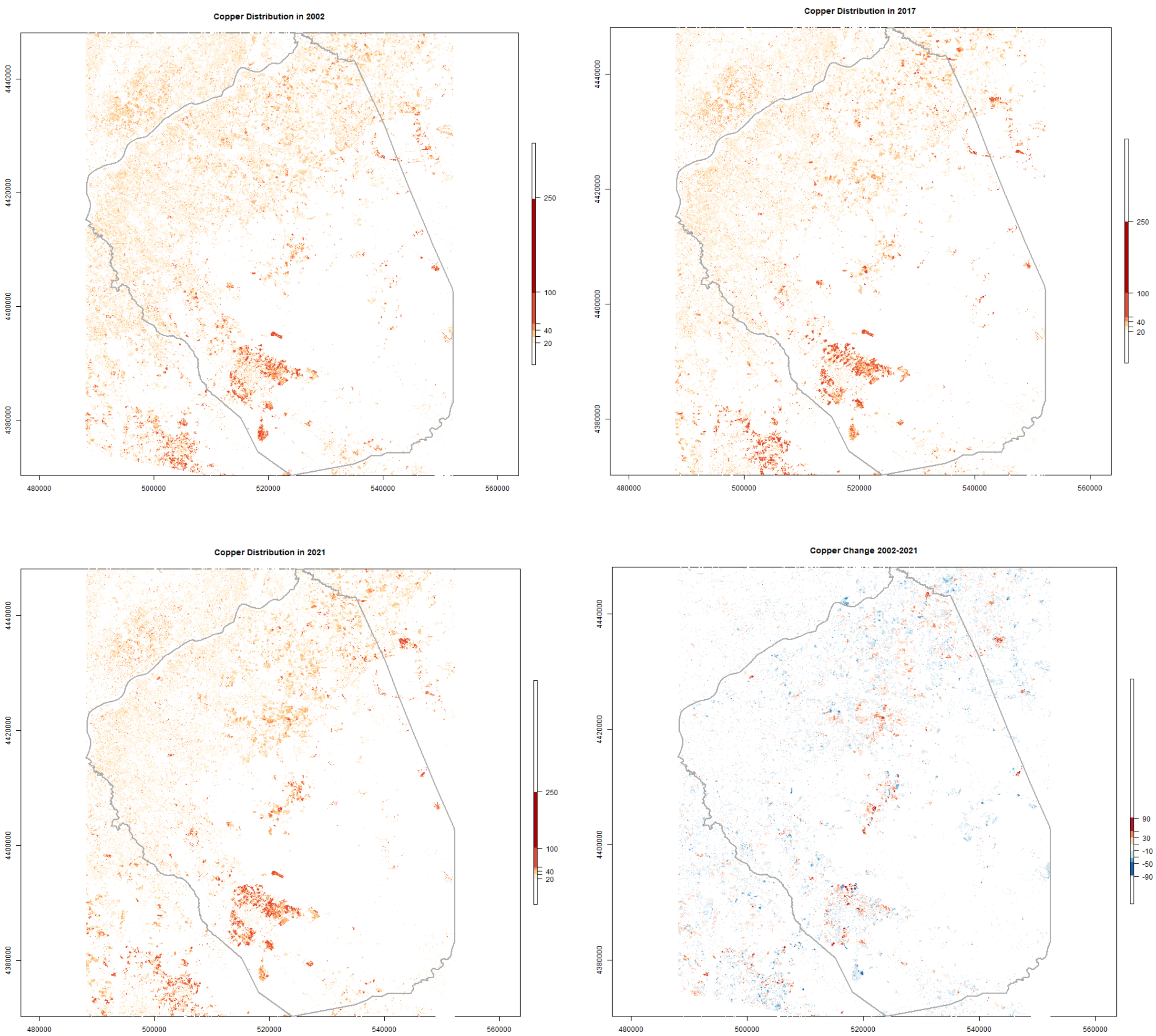


Fig 10a-c. Copper distribution prediction in the study area in 2002 (a), 2017 (b) and 2021 (c); Fig 10d. Copper distribution change from 2002 to 2021

6 Conclusion

Based on the prediction results, the study area faces the issue of Arsenic which exceeds the residential and nonresidential soil cleanup criteria. The distributions of the three heavy metals are quite similar, concentrating in the northern suburban areas and southwestern farmlands within the pine barren region.

With this model built, the study provides a useful and efficient tool to keep detecting the spatial distribution of heavy metal concentration in soil and identifying areas at a higher risk of soil contamination and also analyzing their changes over time, once the latest satellite image bands are input into this model.

Lastly, the model has relatively low accuracy probably because linear regression is the only modeling method used. To improve it further, more methods need to be tested like GA-BP model and M5 model tree, which are used in previous studies. In addition, further research on heavy metal attributes and their movement in the environment could be helpful to understand the mechanism of heavy metal distribution.

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