Hindawi
Journal of Sensors
Volume 2023, Article ID 9792129, 1 page
https://doi.org/10.1155/2023/9792129

Retraction

Retracted: A Monitoring System for Air Quality and Soil Environment in Mining Areas Based on the Internet of Things

Journal of Sensors

Received 13 September 2023; Accepted 13 September 2023; Published 14 September 2023

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] H. Dai, D. Huang, and H. Mao, "A Monitoring System for Air Quality and Soil Environment in Mining Areas Based on the Internet of Things," *Journal of Sensors*, vol. 2022, Article ID 5419167, 7 pages, 2022.

Hindawi
Journal of Sensors
Volume 2022, Article ID 5419167, 7 pages
https://doi.org/10.1155/2022/5419167

Research Article

A Monitoring System for Air Quality and Soil Environment in Mining Areas Based on the Internet of Things

Hongjing Dai, Dena Huang, and Haili Mao

School of Chemistry and Chemical Engineering, Qiannan Normal University for Nationalities, Duyun, Guizhou 558000, China

Correspondence should be addressed to Haili Mao; 20160612@ayit.edu.cn

Received 24 July 2022; Revised 7 August 2022; Accepted 13 August 2022; Published 26 August 2022

Academic Editor: C. Venkatesan

In order to solve the intensifying problem of heavy metal pollution of soil in mining areas, a method for monitoring air quality and soil environment in mining areas based on the Internet of Things is proposed. Using meta-analysis method and health risk assessment method, the impact of mining on soil heavy metal content in Southwest China was quantitatively analyzed, and the relationship between soil heavy metal value and its potential influencing factors was discussed, as well as the heavy metal pollution, ecological risk, and health caused by soil mining activities. Risks were assessed. The results showed that artificial and oral intake were the main modes of soil heavy metal exposure, with the highest daily intakes for noncarcinogenic risk children and the highest daily intakes for carcinogenic risk adult females. The noncarcinogenic risk (HQ>1) of soil As and Pb exposure to children was 3.74 and 1.44, respectively. The carcinogenic risk values of As, Cd, Cr, and Ni in soil were all higher than 10-6, indicating that the carcinogenic risk was within the tolerance range of human body. Children were exposed to the combined noncarcinogenic risk (HI = 3.83), and the risk values of the three types of recipients were 1.19×10^{-4}, 1.21×10^{-4}, and 1.06×10^{-4}, respectively. The correlation between heavy metal content and environmental factors was obtained. It is verified that the system in this paper can effectively monitor the meteorological environment and soil environment, and at the same time, it reveals the pollution law of heavy metals in the soil of the mining area, which provides supporting conditions for future mining and heavy metal pollution management.

1. Introduction

In recent years, the rapid exploitation of mineral resources in China has not only promoted the development of social economy, but also caused serious soil pollution. Soil pollution is a pollution caused by a kind of toxic substances produced as a result of unreasonable human activity through the way such as atmosphere, the earth surface, or underground runoff into the soil. When the soil accumulation exceeds the self-purification capacity of the soil itself, the composition, structure, and function of the soil will change, and microbial activities will be crimped, which can harm human health eventually through the food chain. Data collection is shown in Figure 1 [1]. Heavy metals refer to elements with a density greater than $5\,g\,cm^{-3}$, which gradually accumulate after entering the soil. When exceeding a certain standard, they are absorbed by soil colloid. After physical or chemical reactions, they will form a pollutant. These pollutants cannot be degraded by microorganisms. They have great toxicity, and they are easy to enrich in the soil, resulting in serious soil heavy metal pollution. This kind of pollution has the characteristics of long-term, hidden, and irreversible, which will affect the normal agricultural production and life. It is a kind of soil pollution that is difficult to treat. Researches show that the area of soil heavy metal pollution in China has reached 50 million mu and the content of heavy metals in soil shows a rising trend, mainly Cd (cadmium), Pb (lead), Hg (mercury), and other heavy metals [2]. Heavy metal pollution not only destroys land, but also causes certain harm to human health. For example, excessive intake of Cd will lead to hypertension and cardiovascular and cerebrovascular diseases. Arsenic (As) is recognized as a carcinogenic heavy metal, which has obvious accumulation in the human body. It can cause red blood cell

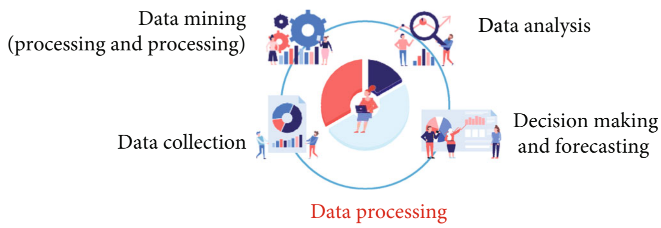

Figure 1: The process of big data processing environmental information.

dissolution, damage normal physiological functions, and can cause cancer and teratogenesis in serious cases. Excessive Pb in children will cause mental decline and growth retardation.

The era of big data has arrived, and big data has been involved in all walks of life. The data resources mastered by all walks of life are important wealth in the future. The government use big data thinking to solve specific problems. The big data thinking and technology are applied in environmental governance to provide data support for environmental public governance. Through data collection, real-time monitoring, the citizen participation in the form of management, and environmental governance, it can provide scientific and accurate thinking for the government decision-making in public environment monitoring and early warning [3].

2. Literature Review

At present, local provinces and cities in China are constantly developing the level of environmental protection information, and they are trying to establish information centers to coordinate environmental data resources. Ahmad et al. summarized the technologies involved in the application of environmental big data [4]. In the platform category, the local platform architecture mainly included Hadoop and Map R. The cloud architecture mainly included AWS and Azure. In the database category, the SQL category included Greenplum, No SQL category included HBase, and New SQL included Spanner. Data warehouse technology included Hive. In data processing, batch processing technologies included Map Reduce, and data flow processing technologies included Storm. Query languages included Hive QL. Machine learning included Mahout. And log processing included Splunk. Yang et al. summarized the key technologies of industrial energy and environment big data [5]. They put forward that big data was a long industrial chain. Data collection stage mainly based on industrial Internet of Things technology. Data preprocessing stage included data extraction and cleaning. Big data storage and management phase included development of distributed file system optimization storage, innovation of database technology, and maintenance of big data security. Data analysis and mining stage mainly developed various machine learning algorithms and database methods. In the parallel stage of data computation, Hadoop architecture should be adopted. FLASH and other ways were adopted to achieve data visualization. Hamidović et al. emphasized the importance of heterogeneous data sources in environmental big data. They proposed that the real environmental big data should break the traditional data sources, namely the data of environmental departments themselves, and related departments included more emerging Internet data and smart facility data [6].

In the research, the process of big data technology was attempted to apply in environmental monitoring and early warning. Combining theoretical knowledge and empirical practice, the environmental big data was established in the field of public governance environment. Through specific case analysis, in view of the environmental problems, environmental public service solution and effective governance based on large data was put forward. By using big data in high efficiency value in the process of management decision, environmental big data was established, and environmental big data system and governance mechanism were formed, providing a constructive reference for the government in the construction of basic environmental public services. It helped government departments to carry out accurate regulation and optimize the government's environmental public service level [7, 8].

By using meta-analysis method and health risk assessment method, the quantitative analysis of the mining impact on soil heavy metal content in Southwest China was made, the effect of the relationship between soil heavy metals value and its potential impact factors was discussed, and the soil heavy metal pollution, the ecological risk, and the health risk caused by mining activities were evaluated. In the research, the carcinogenic risk caused by heavy metal pollution in mining area was analyzed to solve the problem of analyzing the harm caused by soil heavy metal pollution to human body.

3. Research Methods

3.1. Meta-analysis. In meta-analysis, the collected data were divided into two groups according to the treatment group and the control group, and pairwise pairing was performed. By using model calculation method, the relationship between the treatment group and the control group was expressed by a numerical value, which was the effect size (ES). In the research, the background values, sampling numbers, and standard deviations of heavy metals in soils of Southwest China recorded by China Environmental Monitoring Station (1990) were selected as the control group. The mean value, sampling quantity, and standard deviation of soil heavy metal content extracted in the literature survey were the treatment group [9, 10]. In the research, logarithmic reaction ratio $(\ln R)$ was used to measure the effect value. And its calculation formula was as follows.

$$ES = \ln R = \ln \left(\frac{X_t}{X_c} \right) = \ln (X_t) - \ln (X_c). \tag{1}$$

In Formula (1), X_t represented the average value of soil heavy metals extracted from the literature. X_c represented the background value of heavy metals in soils of provinces in Southwest China. If the effect value was higher than 0, it indicated that mining increased the content of heavy metals in soil. The intrastudy variance (v_i) corresponding to each effect value could be calculated using the following formula.

$$v_i = \frac{S_t^2}{N_t X_t^2} + \frac{S_c^2}{N_t X_t^2}. \tag{2}$$

In Formula (2), S_t and S_c were the standard deviations (SD) of the mean value and background value of soil heavy metals. N_t and N_c were the number of heavy metal groups in soil survey of the control group and the treatment group, respectively. In meta-analysis, there were two types of models: fixed effect and random effect. The former only took into account intrastudy differences, while the latter took into account both intrastudy and interstudy differences. The soil heavy metals in mining areas investigated in the research were located in different geographical locations and natural environments, and there were certain differences between studies. Therefore, the random effect model was selected to calculate its effect value [11, 12]. This model took into account not only intrastudy variance but also interstudy variance ($\tau 2$), which was estimated by maximum likelihood function (REML). The weight w_i of each study was calculated as follows:

$$w_i = \frac{1}{v_i + \tau^2}. \tag{3}$$

The weighted w_i of each study could be used to calculate the comprehensive effect value (ES_+) after weighted average. And the calculation formula was as follows:

$$ES_+ = \frac{\sum_{i=1}^{k} (w_i + ES_I)}{\sum_{i=1}^{k} w_i}. \tag{4}$$

In Formula (4), w_i and ES_i were the weighted and unweighted effect value of the ith pair of data, respectively. k was the number of pairs between the control group and the treatment group. At the same time, the 95% confidence interval (CI) of the comprehensive effect value was calculated. If the 95% confidence interval (CI) of the comprehensive effect value was greater than 0, it was believed that the mining in Southwest China had a significant increase in the content of heavy metals in soil ($p < 0.05$). If 95% confidence intervals were all less than 0, mining in Southwest China did not significantly increase the content of heavy metals in soil ($p < 0.05$). If the 95% confidence interval contained 0, it was believed that mining in Southwest China had no significant impact on the content of heavy metals in soil ($p < 0.05$) [13, 14]. In order to more conveniently explained the influence of mining on the content of heavy metals in soil in Southwest China, the percentage change of the content was calculated by the following formula:

$$PI = \left(e^{ES_+} - 1 \right) \times 100\%. \tag{5}$$

3.2. Health Risk Assessment Method. The health risks were assessed by using a National Environmental Protection Agency health risk assessment model, which linked soil heavy metal pollution with human health and quantitatively assessed the health risks of the exposed recipients. Carcinogenic and noncarcinogenic risks were quantified based on daily heavy metal intake in children, adult women, and adult men. The calculation methods of daily intake under skin contact (ADI_{der}), hand-oral intake (ADI_{ing}), and oral-nasal respiration (ADI_{inh}) were as follows, and the specific meanings of parameters are shown in Table 1.

$$ADI_{der} = \frac{C \times SA \times ABS \times AF \times EF \times ED \times CF}{BW \times AT}, \tag{6}$$

$$ADI_{ing} = \frac{C \times IR \times EF \times ED \times CF}{BW \times AT}, \tag{7}$$

$$ADI_{inh} = \frac{C \times InhR \times EF}{PEF \times BW \times AT}. \tag{8}$$

The noncarcinogenic risk was expressed by the hazard quotient (HQ) of heavy metals, and the comprehensive noncarcinogenic risk was expressed by the total hazard index (HI) of individual heavy metals. Rfd_{der}, Rfd_{ing}, and Rfd_{inh} were the reference doses [mg $(kg\,day)^{-1}$] of heavy metal intake in skin contact, hand-oral intake, and oral-nasal respiratory exposure, respectively. The reference values are shown in Table 2. If HQ or $HI < 1$ indicated that there was no noncarcinogenic risk, otherwise, heavy metal exposure presented a noncarcinogenic risk. The comprehensive noncarcinogenic risk calculation formula was as follows.

$$HI = \sum_{i=1} HQ_i = \sum \left(\frac{ADI_{der}}{Rfd_{der}} + \frac{ADI_{ing}}{Rfd_{ing}} + \frac{ADI_{inh}}{Rfd_{inh}} \right). \tag{9}$$

The carcinogenic risk (CR) was the possibility of developing cancer after exposure to soil heavy metals in the whole life cycle. SF_{der}, SF_{ing}, and SF_{inh} were soil heavy metal carcinogenic tilt factors [mg $(kg\,day)^{-1}$] under skin contact, hand-oral ingestion, and oral-nasal respiratory exposure, respectively. See Table 2 [15, 16]. If $CR < 10^{-6}$, there was no carcinogenic health risk. Between 10^{-6} and 10^{-4} was the range of

Table 1: Parameter significance and selected values of daily intake of heavy metals in soil.

Parameter	Meaning	Unit	Child	Adult	
				Female	Male
C	Heavy metal content	mg kg^{-1}			
SA	Skin surface area exposed to soil	cm^{2}	9310	15310	16970
ABS	Skin absorption factor	Dimensionless	0.001	0.001	0.001
AF	Adhesion coefficient of soil to skin	mg (cm^{2} day)$^{-1}$	0.2	0.07	0.07
EF	Exposure frequency	Day year^{-1}	345	345	345
ED	Exposed fixed number of year	Year	6	24	24
CF	Conversion factor	kg mg^{-1}	10^{-6}	10^{-6}	10^{-6}
InhR	Daily respiration rate	m^{3} day^{-1}	11.78	14.17	19.02
IR	Soil digestibility	mg day^{-1}	200	100	100
BW	Weight	kg	27.7	54.4	62.7
PEF	Particulate emission factor	m^{3} kg^{-1}	1.36×10^{9}	1.36×10^{9}	1.36×10^{9}
AT	Average non-carcinogenic time	Day	ED × 365	ED × 365	ED × 365
	Average time to carcinogenesis	Day	25550	25550	25550

Table 2: Reference doses and carcinogenic tilt factors of soil heavy metals exposed by different pathways [mg(kg day)$^{-1}$].

	Rfd_{der}	Rfd_{ing}	Rfd_{inh}	SF_{der}	SF_{ing}	SF_{inh}
As	1.23×10^{-4}	3×10^{-4}	3×10^{-4}	3.66	1.5	15.1
Cd	1×10^{-5}	1×10^{-3}	1×10^{-3}	6.3	6.1	6.3
Cr	6×10^{-5}	3×10^{-3}	2.86×10^{-5}	20	0.5	42
Cu	1.2×10^{-2}	4×10^{-2}	4.02×10^{-2}	—	—	—
Hg	2.1×10^{-5}	3×10^{-4}	8.57×10^{-5}	—	—	—
Ni	5.4×10^{-3}	2×10^{-2}	9×10^{-5}	42.5	1.7	0.84
Pb	5.25×10^{-4}	3.5×10^{-3}	3.52×10^{-3}	—	8.5×10^{-3}	—
Zn	6×10^{-2}	0.3	0.3	—	—	—

Note: —: no parameter.

human tolerable cancer risk; higher than 10^{-4} indicated the existence of serious carcinogenic health risks, which should be paid attention to. The comprehensive carcinogenic risk calculation formula was as follows.

$$TCR = \sum_{i=1} CR_i = ADI_{der} \times SF_{der} + ADI_{ing} \times SF_{ing} + ADI_{inh} \times SF_{inh}. \tag{10}$$

4. Results Analysis

4.1. Descriptive Statistics and Spatial Distribution of Heavy Metal Content in Soil. The descriptive statistics of soil heavy metals in Southwest China are shown in Table 3. The average contents of heavy metals except Cr and Ni exceeded the national risk screening values of soil Environmental Quality Standards for corresponding agricultural lands (GB15618-2018). The average of soil As and Cd contents exceeded the national risk control value (Table 3). The overstandard rates of As, Cd, Cr, Cu, Hg, Ni, Pb, and Zn (the percentage of the number of investigation groups exceeding the national risk screening value in the total investigation group) were 75.58%, 82.93%, 2.78%, 46.24%, 32.61%, 4.35%, 63.49%, and 50.43%, respectively. Among them, soil Cd had the highest overstandard rate, and its average overstandard multiple was 16.22. Soil As and Pb had higher overstandard rate, with overstandard multiple of 8.20 and 4.31, respectively. The exceedance rate of Cr and Ni in soil was less [17, 18]. The median of each heavy metal content was lower than the average value, and the 95th percentile value differed greatly from the maximum value, which exceeded the corresponding control value (Table 3). This indicated that the mining of mineral resources in Southwest China led to a certain accumulation of heavy metals in soil, among which Cd accumulation was the most and Cr accumulation was the least. The results showed that the distribution area of high content in soil was not only related to soil high background value, but also related to mining. Mineral resources were widely distributed in these areas, and a large number of heavy metal elements were released in the mining process, so the distribution of heavy metals showed obvious similar regional spatial distribution characteristics. As a whole, the content of heavy metals in soil around mining area in Southwest China was relatively high.

4.2. Influence of Mining on Soil Heavy Metals under Different Land Use Types in Southwest China. Table 4 shows the parameter significance of the influence factors of soil heavy metals investigated in the mining area in Southwest China. The land use types investigated in the research mainly included abandoned land soil, arable land soil, and woodland soil. On the whole, the average effect of mining on heavy metals under different land use types from high to low was as follows: wasteland soil > cultivated soil > woodland soil (Table 4). The average effect value of heavy metals in soil of abandoned mining areas was 2.59 (Table 4). Compared with soil background value, its content increased by 1232.98%. The average effect of mining on cultivated land and forest land was 1.43 (95% CI: 1.30–1.56) and 0.87

Table 3: Descriptive statistics of soil heavy metals in mining areas in Southwest China extracted from the literature (mg kg^{-1}).

	Minimum	25 percentile	Median	Mean	75 percentile	95 percentile	Maximum	Screening value a	Regulated value a
As	4.8	20.59	38.03	164.01	155.64	477.58	2423.57	20	100
Cd	0.19	1.03	3.46	9.73	11.15	46.53	66.17	0.6	4
Cr	18.06	50.92	82.45	101.13	125.95	186.13	683.57	250	1300
Cu	9.69	41.45	88.43	214.62	148	457.33	4480.87	100	—
Hg	0.06	0.22	0.59	3.12	1.27	18.84	35.1	1	6
Ni	12.87	36.41	57.8	74.72	74.25	164.55	656.11	190	—
Pb	9.44	72.65	250	732.14	748.39	2650.86	8816.34	170	1000
Zn	24.26	129.52	311.9	1483.57	1485.06	4924.12	36995.2	300	—

Note: Soil Environmental Quality Standard (GB15618-2018); descriptive statistics were obtained from the average of soil heavy metal content extracted from literature.

Table 4: Parameter significance of influencing factors of soil heavy metals in the survey location of the mining area in Southwest China.

Influencing factors		Number of observation group	Effect value	Upper limit	Lower limit	Heterogeneity
Land use type	Soil	33	0.87	0.34	1.40	$Q_m = 567.38$, df = 3, ($p < 0.0001$)
	The soil	531	1.43	1.30	1.56	
	Abandoned soil	38	2.59	2.10	3.09	
Minerals	Non-ferrous ore	538	1.70	1.57	1.82	$Q_m = 691.83$, df = 3, ($p < 0.0001$)
	Coal mine	123	0.65	0.38	0.92	
	Ferrous ore	46	0.54	0.10	0.98	
Geographical partition	A	323	1.83	1.66	1.99	$Q_m = 678.03$, df = 5, ($p < 0.0001$)
	B	72	1.81	1.46	2.16	
	C	280	0.93	0.75	1.11	
	D	10	1.43	0.48	2.37	
	E	22	0.94	0.31	1.58	

Note: Q_m is the heterogeneity caused by this influencing factor. Df is the degree of freedom. $p < 0.05$ shows that the influence of this factor is significant. The upper limit and lower limit are the maximum and minimum value of 95% confidence interval, respectively. The number of observation group refers to the number of heavy metal groups investigated.

(95% CI: 0.34–1.40), respectively (Table 4). This showed that arable land was more affected by mining activities than forest land. Figure 2 shows the effects of mining on soil heavy metals under different land use types in Southwest China, which showed that the influence of mining on abandoned land was higher than that of arable land and woodland soil. In arable soil, Cd (2.60), Hg (2.19), and Pb (1.86) were mainly affected by mining, and the effect values of Cd (2.60), Hg (2.19), and Pb (1.86) were higher (Figure 2). Compared with the background value, the content increased by 1246.37%, 793.52%, and 542.37%, respectively.

4.3. Influence of Mining on Soil Heavy Metals in Different Provinces in Southwest China. Table 5 shows the overall heterogeneity of heavy metals in soils of mining areas in Southwest China. The p value of overall heterogeneity ($Q_t = 129330.05, p < 0.0001$) of soil heavy metals caused by mining in Southwest China was lower than 0.05. As can be seen from Table 5, the significance level (p value) of the overall heterogeneity of individual heavy metals was all less than 0.05, so it was necessary to introduce explanatory variables for analysis [19, 20]. The number of heavy metal groups in A, B, C, D, and E and Xizang were 323, 72, 280, 22 and 10, respectively. According to the survey statistics, except Cr, mining in A mine significantly increased the con-

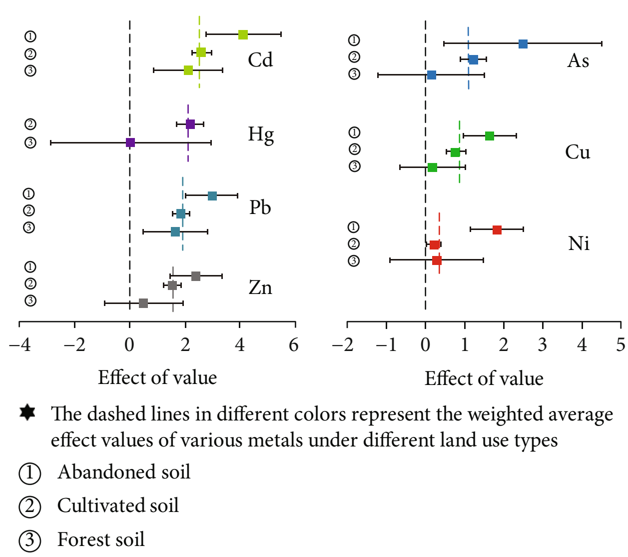

Figure 2: Influence of mining on heavy metals under different land use types in Southwest China.

tents of other heavy metals. The average effect values of Cd, Pb, Zn, and As in soil were 3.21, 2.33, 1.75, and 1.45, respectively. Compared with the background value, the heavy

Table 5: Overall heterogeneity of all heavy metals caused by mining in Southwest China.

Heavy metals	As	Cd	Cr	Cu	Hg	Ni	Pb	Zn
Q_t	8128.49	8290.86	4169.17	7437.63	4101.64	1339.61	30428.23	27456.61
p	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001

Note: Q_t represents the overall heterogeneity of the data and p represents the level of significance.

metal content in the samples increased by 2377.91%, 927.79%, 326.31%, and 475.46%, respectively. The mining of a mine significantly increased Cd (3.78), Pb (2.96), Zn (2.27), and Hg (1.75) in soil than the other four heavy metals. Compared with soil background value, its content increased by 4281.6%, 1829.8%, 867.94%, and 475.46%, respectively. The mining of B and C both resulted in a high increase of Hg in soil. In Guizhou mining, soil Hg (2.49) had the highest effect value, while soil Cu (0.25) had the lowest. Compared with the background value, the content of Hg in soil increased by 1106.13%. Mining in Chongqing also significantly increased the content of Hg in soil, with an effect value of 2.14.

4.4. Evaluation of Ground Accumulation Index of Heavy Metal Content in Soil by Mining. The evaluation results showed that the average ground accumulation index of the eight heavy metals from high to low was Cd > Hg > Pb > Zn > As > Cu > Ni > C. The pollution degree of heavy metals in soil caused by mining was different. Cd was strongly polluted. Hg and Pb were moderately to strongly polluted. Zn and As were moderately polluted. Cu was slightly polluted. Ni and Cr were pollution-free. The evaluation results of potential ecological risk index showed that the average ecological risk index of 8 heavy metals from high to low was Cd/Hg > Pb/As > Cu/Zn/Ni/Cr. Soil heavy metals Cd and Hg were in extremely strong ecological risk, and the risk degree was higher than other heavy metals. The comprehensive ecological risk of soil heavy metals was extremely high, accounting for 39.72%, and Cd and Hg were the main contributing factors to the ecological risk. The results of health risk assessment showed that manual and oral intake was the main way of soil heavy metal exposure, with the highest daily intake for children under noncarcinogenic risk and the highest daily intake for adult women under carcinogenic risk. The exposure of soil As and Pb had a noncarcinogenic risk to children, with a risk value of 3.74 and 1.44, respectively. The carcinogenic risk values of As, Cd, Cr, and Ni in soil were all higher than 10^{-6}, indicating that the carcinogenic risk was within the tolerance range of human body. Children were affected by the combined non-carcinogenic risk, and the risk values of all three types of recipients were 1.19×10^{-4}, 1.21×10^{-4}, and 1.06×10^{-4}, respectively.

Based on the results, As, Cd, Hg, and Pb should be prioritized in the mining area of Southwest China. Children are a priority group of residents. Compared with the previous studies on soil heavy metals in single mining areas and a few mining areas, the above results can provide more effective decision support for soil pollution prevention and control and soil environmental quality protection in mining areas in Southwest China.

5. Conclusion

In the research, by using meta-analysis method and health risk assessment method, the quantitative analysis of the mining impact on soil heavy metal content in Southwest China was made, the effect of the relationship between soil heavy metals value and its potential impact factors was discussed, and the soil heavy metal pollution, the ecological risk, and the health risk caused by mining activities were evaluated. To a certain extent, the research results quantitatively assessed the impact of mining on soil heavy metals in Southwest China. Although some meaningful conclusions have been drawn, there are also shortcomings, mainly in the following aspects.

(1) The fact that heavy metal content in the soil accumulates or increases is influenced by many factors, which is not just mentioned in the research. There are many other possible factors, such as pH, soil organic carbon, and mine production. The relevant data involved in the investigation is less, which is not easy to extract and need more case researches. Therefore, it has not yet been discussed in the research, and these factors should be taken into account in future research

(2) The impact of soil heavy metal pollution on human body is not only related to the amount of heavy metal exposure, but also related to the biological availability of heavy metals ingested by human body, which should be paid attention to in future research

Mining has promoted the development of local economy, but the pollution of heavy metals in mining soil has also affected the normal production and life of human beings. And the accumulation of heavy metals in soil is also a relatively complex process. In the future further analysis, in addition to analyzing the increase of soil heavy metals caused by mining, comprehensive consideration should be given to the migration mechanism and form existence of heavy metals themselves in the soil, so as to provide more and more effective information for improving soil environmental quality and building green mines.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] M. S. Askari, P. Alamdari, S. Chahardoli, and A. Afshari, “Quantification of heavy metal pollution for environmental assessment of soil condition,” *Environmental Monitoring and Assessment*, vol. 192, no. 3, pp. 1–17, 2020.

[2] W. M. Badawy, Y. Sarhan, O. G. Duliu et al., “Monitoring of air pollutants using plants and co-located soil – Egypt: characteristics, pollution, and toxicity impact,” *Environmental Science and Pollution Research*, vol. 29, no. 14, pp. 21049–21066, 2022.

[3] A. L. Sikora, L. W. Maguire, R. W. Nairn, and R. C. Knox, “A comparison of XRFS and ICP-OES methods for soil trace metal analyses in a mining impacted agricultural watershed,” *Environmental Monitoring and Assessment*, vol. 193, no. 8, pp. 1–20, 2021.

[4] T. Ahmad, S. Nazar, K. Ahmad et al., “Monitoring of copper accumulation in water, soil, forage, and cows impacted by heavy automobiles in Sargodha, Pakistan,” *Environmental Science and Pollution Research*, vol. 28, no. 23, pp. 29110–29116, 2021.

[5] H. Yang, H. Xu, and X. Zhong, “Study on the hyperspectral retrieval and ecological risk assessment of soil Cr, Ni, Zn heavy metals in tailings area,” *Bulletin of Environmental Contamination and Toxicology*, vol. 108, no. 4, pp. 745–755, 2022.

[6] S. Hamidović, G. G. Cvijović, H. Waisi et al., “Response of microbial community composition in soils affected by coal mine exploitation,” *Environmental Monitoring and Assessment*, vol. 192, no. 6, p. 364, 2020.

[7] F. Li, X. Zhang, A. Lu, L. Xu, D. Ren, and T. You, “Estimation of metal elements content in soil using x-ray fluorescence based on multilayer perceptron,” *Environmental Monitoring and Assessment*, vol. 194, no. 2, p. 95, 2022.

[8] C. Zheng, H. Liao, and C. Tu, “An improved bibliometric analysis on antibiotics in soil research,” *Bulletin of Environmental Contamination and Toxicology*, vol. 108, no. 2, pp. 276–283, 2022.

[9] S. Mentese, Ö. T. Yayintas, B. Bas, L. C. İrkin, and S. Yilmaz, “Heavy metal and mineral composition of soil, atmospheric deposition, and mosses with regard to integrated pollution assessment approach,” *Environmental Management*, vol. 67, no. 5, pp. 833–851, 2021.

[10] S. B. Turhan, I. Oruc, and H. Ozdemir, “Impact of heating season on the soil pollution in Kirklareli province of Turkey,” *Environmental Monitoring and Assessment*, vol. 193, no. 4, pp. 1–15, 2021.

[11] B. Chai, Q. Wei, Y. She, G. Lu, Z. Dang, and H. Yin, “Soil microplastic pollution in an e-waste dismantling zone of China,” *Waste Management*, vol. 118, no. 19, pp. 291–301, 2020.

[12] G. Soubra, M. A. Massoud, I. Alameddine, M. al Hindi, and C. Sukhn, “Assessing the environmental risk and pollution status of soil and water resources in the vicinity of municipal solid waste dumpsites,” *Environmental Monitoring and Assessment*, vol. 193, no. 12, p. 857, 2021.

[13] M. Fan and A. Sharma, “Design and implementation of construction cost prediction model based on SVM and LSSVM in industries 4.0,” *International Journal of Intelligent Computing and Cybernetics*, vol. 14, no. 2, pp. 145–157, 2021.

[14] I. Ilechukwu, L. C. Osuji, C. P. Okoli, M. O. Onyema, and G. I. Ndukwe, “Assessment of heavy metal pollution in soils and health risk consequences of human exposure within the vicinity of hot mix asphalt plants in rivers state, Nigeria,” *Environmental Monitoring and Assessment*, vol. 193, no. 8, p. 461, 2021.

[15] A. Rajendran, N. Balakrishnan, and P. Ajay, “Deep embedded median clustering for routing misbehaviour and attacks detection in ad-hoc networks,” *Ad Hoc Networks*, vol. 126, article 102757, 2022.

[16] B. S. Ferreira, M. S. S. Almeida, F. R. Lopes, M. do Carmo Reis Cavalcanti, and C. J. P. Filho, “On the use of random material in dam cores: case of the Manso dam, Brazil,” *Geotechnical and Geological Engineering*, vol. 40, no. 4, pp. 1973–1987, 2022.

[17] X. Liu, J. Liu, J. Chen, and F. Zhong, “Mn_2O_3/γ-Al_2O_3 catalysts synergistic double dielectric barrier discharge (DDBD) degradation of toluene, ethyl-acetate and acetone,” *Chemosphere*, vol. 284, article 131299, 2021.

[18] R. Huang, S. Zhang, W. Zhang, and X. Yang, “Progress of zinc oxide-based nanocomposites in the textile industry,” *IET Collaborative Intelligent Manufacturing*, vol. 3, no. 3, pp. 281–289, 2021.

[19] P. Ajay, B. Nagaraj, R. A. Kumar, R. Huang, and P. Ananthi, “Unsupervised hyperspectral microscopic image segmentation using deep embedded clustering algorithm,” *Scanning*, vol. 2022, Article ID 1200860, 9 pages, 2022.

[20] G. Veselov, A. Tselykh, A. Sharma, and R. Huang, “Applications of artificial intelligence in evolution of smart cities and societies,” *Informatica (Slovenia)*, vol. 45, no. 5, p. 603, 2021.