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Study on heavy metal content calculation and agricultural potential using hyperspectral remote sensing image processing

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Abstract: Soil is the main influencing factor for plant growth, reproduction, and distribution. With the acceleration of industrialization and the intensification of human activities, the problem of heavy metal pollution in agricultural soil is becoming increasingly prominent. Heavy metals present in soil are toxic and readily absorbed by plants, posing a significant threat to human health when contaminated crops are consumed. Therefore, monitoring the content of heavy metals (referred to as HMs) in soil is imperative. Hyperspectral remote sensing (HRS), owing to its ultrahigh spectral resolution, holds significant promise for acquiring quantitative information on soil organic matter, minerals, and other components. In comparison with traditional detection methods, soil heavy metal inversion based on HRS offers advantages such as rapid, convenient, and large-scale on-site monitoring, demonstrating considerable practical value. This study investigates the monitoring mechanism and feature extraction of HRS technology by analyzing the calculation methods for soil and HM content. In the experimental phase, the HM content in rice and corn crops, paddy soil, and lime soil from 2017 to 2020 was analyzed. Through experimental comparative analysis, it was observed that the HMs enrichment coefficients were 0.987, 1.154, and 0.186 in 2017, 2018, and 2020, respectively. Notably, the smallest HMs enrichment coefficient was recorded in 2020, while the highest was in 2018. The utilization of HRS image processing enhances the accuracy of HM content determination, thus bearing significant implications for assessing soil agricultural potential.

Key words: Heavy metal content, agricultural potential analysis, hyperspectral remote sensing, image processing, radial basis function

1. Introduction

With the rapid development of the social economy, significant quantities of heavy metals (HMs) are being released into agricultural soil environments, resulting in HM pollution in these soils. Heavy metals, defined as metals with a density exceeding 4.5 g/cm^3, include gold, silver, copper, iron, mercury, lead, cadmium, among others. Accumulating to certain levels in the human body, HMs can induce chronic poisoning. Soil serves as the substrate for crop growth, and elevated HM concentrations beyond environmental tolerance thresholds can impede chlorophyll synthesis in crops, leading to alterations in the spectral characteristics of crop leaves and canopies. Thus, detecting HMs in soil can be accomplished by analyzing hyperspectral data from crop canopies and leaves, complemented by various spectral indices. Leveraging hyperspectral remote sensing (HRS) technology, real-time and rapid monitoring of HM fluctuations in farmland soil and crops holds immense importance for ensuring food safety and safeguarding public health.

HM pollution poses significant threats to both soil and human health, underscoring the importance of studying HM content to analyze soil agricultural potential. Consequently, numerous scholars have undertaken HM content calculations. For instance, Lian-Fang Li collected 124 soil samples from greenhouse vegetable cultivation, corn fields, and forest soils across different land use patterns within a typical greenhouse vegetable production system (Li et al., 2018). Ebrahim Alinia-Ahandani presented chemical analyses of lead, nickel, chromium, and copper total contents in soil samples, revealing that these exceeded permissible limits (Alinia-Ahandani et al., 2020). Naznin Nahar conducted a carrot pot experiment to explore soil properties, growth patterns, and HM absorption by carrots postsewage sludge application (Nahar, 2021). Investigating HM pollution status in agricultural soils, Xuezhen Li employed spatial autocorrelation methods to unveil HM accumulation distributions, along with reviewing and synthesizing literature on HM soil pollution (Li et al., 2018). Salman A. Salman analyzed soil sample

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physical and chemical characteristics using pollution factors, pollution degree, pollution load index, ecological risk factor, potential ecological risk index, and geological accumulation index (Salman et al., 2019). Mamdouh Alsayed Eissa conducted field and laboratory studies to assess HM concentrations in the edible parts of lettuce and spinach plants irrigated with sewage, revealing soil contamination with HMs (Eissa and Negim, 2018). To investigate spatial variability and pollution risks of HMs in Dianthus soil and promote sustainable Dianthus industry development, Hong-Ju Zhang selected Lin'an, a typical Dianthus planting area, for investigation (Hong et al., 2017). V. I. Lopushniak aimed to evaluate Jerusalem artichoke's HM absorption capability in oil-contaminated ecosystems, focusing primarily on oil and gas pipeline areas (Lopushniak and Hrytsuliak, 2021). While these studies have described HM soil content calculations, none have specifically addressed soil agricultural potential analysis.

Ensuring scientific and accurate agricultural decision-making hinges on the assessment and identification of agricultural data quality. High-quality agricultural data not only guides production practices and supports scientific research but also aids governmental decision-making processes. Weed identification plays a crucial role in crop yield optimization and the realization of precision agriculture. To address this, a method based on heterogeneity is proposed. This method involves selecting a small yet representative sample, fully considering data diversity, and developing an efficient crop-weed classification system (Yang et al., 2022). Additionally, a method for determining the embedding range in the feature space and conducting numerous comparative experiments has been proposed. Results indicate that, in certain recognition tasks, selecting a small subset of good-quality data can achieve performance comparable to using all training data, thus laying the foundation for data and information analysis in smart agriculture (Li et al., 2021).

A new data quality evaluation method, termed k-nearest neighbor distance entropy (KNN-DE), is proposed for assessing crop pest images, filtering informative data, and facilitating efficient pest identification tasks. This approach offers a data-centric research perspective and establishes the groundwork for data quality evaluation (Li et al., 2023). Moreover, a simple yet effective method for evaluating data quality, termed interference entropy, has been proposed. Specifically designed for image classification tasks, this method statistically represents existing samples of each category as pixel prototypes to perturb unseen samples (Li et al., 2022). Bai et al. introduced a novel method for identifying atypical breast cancer mammography images based on the ZFNet network. Preprocessing steps' effectiveness can be evaluated using Wiener and CALHE filters, followed by modification and training of the pre-trained ZFNet on the CBIS-DSM dataset. Additionally, Extreme Learning Machines (ELMs) can replace the remaining layers (Bai et al., 2024). Nie Jing explored the application of artificial intelligence and digital twin technology in smart agriculture, discussing challenges and future directions. The study found that digital twins hold substantial potential for success in sustainable agriculture, offering significant implications for low-cost, high-precision smart agriculture solutions (Nie et al., 2022). Wang Y systematically outlined data collection, mining, evaluation, classification, and sustainable algorithm applications in sustainable agricultural computing, offering guidance for future research and development (Nie et al., 2022).

To achieve rapid, nondestructive, and real-time monitoring of HMs in soil and crops, thus ensuring soil environmental quality and food security, this study utilizes hyperspectral data from a specific region spanning 2017 to 2020. Neural network algorithms are employed to analyze HMs enrichment coefficients of soil and agricultural crops under HRS technology. The heavy metal enrichment coefficient serves as a critical index for evaluating organisms' ability to accumulate heavy metal elements, with significant implications for environmental protection and ecological security. Through the research and application of heavy metal enrichment coefficients, timely detection and monitoring of heavy metal pollution in the environment can be achieved, assessing the biological effectiveness of heavy metal elements in the ecosystem, and providing a scientific basis for environmental management and ecological restoration. Experimental investigation and analysis of HM content in HRS images reveal extremely high zinc content and very low mercury content in crops.

2. Detection of HM content in soil and crops

To mitigate long-term health risks and HM pollution, measures should be taken to minimize human activities in soil areas (Latif et al., 2018). Detection of HM content in soil and crops can be categorized into two types: traditional detection and novel methods.

2.1. Traditional testing

Traditional detection methods include optical testing, electrochemical detection, and biological detection (Kandhro, 2023; Hussain, 2022). Soil particle size stands out as a pivotal factor influencing the environmental behavior of HMs (Huang et al., 2020). Conventional soil HM pollution monitoring relies on physical, chemical, and other techniques to acquire instantaneous pollution data of the contaminated object, allowing for the determination of its type, cause, and severity (Uddin, 2022). Nonetheless, this process often entails damage to the contaminated object (soil, agricultural crops, etc.). In addition, due to the limited capability of existing soil HM detection methods to comprehensively analyze farmland soil's ecological environment information, developing a straightforward and efficient soil HM pollution monitoring technology remains challenging.

2.2. New detection

2.2.1. HRS monitoring

HRS technology can perform hyperspectral analysis of surface targets through sensors, with high-resolution and multiband spectra, thus achieving quantitative analysis of HMs in environments such as soil and crops.

2.2.2. Biomass

The biomass method relies on the luminescence characteristics of various biological genes during their expression process, and the light signal can form a spectrum obtained from HRS, thereby quantifying the content of the substance to be tested. The biomass method is currently the most widely used method, with the advantages of being direct, clear, and technically simple. It is calculated based on parameters such as biomass per unit area, forest area, distribution ratio of biomass in various organs of trees, and average carbon content of various organs of trees.

2.2.3. Environmental magnetism

For the calculation and detection of heavy metal content in a region, numerous methods exist, ranging from traditional monitoring approaches to the latest detection techniques. However, this paper opts for HRS technology as the preferred method for heavy metal content detection. The choice of HRS technology is primarily motivated by its ability to swiftly acquire heavy metal content data over large areas. Compared to traditional laboratory determination methods, HRS technology can save considerable time and manpower costs. Furthermore, it facilitates the acquisition of continuous monitoring data in a short timeframe, enabling timely identification of changes in heavy metal content and aiding in prompt problem detection and resolution.

3. Monitoring mechanism and feature extraction of HRS technology

3.1. Monitoring mechanism of HRS technology

HRS technology is a new type of remote sensing technology that integrates precision optics, weak signal detection, detectors, information processing, and computers. HRS technology has the following unique features compared to traditional remote sensing technology. Firstly, it offers a wide array of frequency bands, providing hundreds of options in the visible and near-infrared bands. Secondly, it boasts high spectral resolution ability. The spectrometer has a very small sampling interval, usually 10 nm. Thirdly, it exhibits high spatial resolution capabilities. With ongoing advancements in computer software, data analysis methods, and sensor technology, HRS technology is bound to find even broader application prospects. In addition, through spectral reconstruction, HRS can obtain approximately continuous spectral reflectance data of land features, which matches with ground-measured values, and thus apply fine spectral models of land feature components to land feature information extraction. Both unmanned and manned aerial vehicle-based hyperspectral remote sensing can detect diagnostic ground spectral absorption substances. Leveraging various algorithms, it can not only provide accurate data support for distinguishing surface feature types, evaluating component content but also enables quantitative or semiquantitative feature information extraction possible.

3.1.1. Direct monitoring of soil HM pollution

Based on continuous hyperspectral data collected from soil across the visible, near-infrared, midinfrared, and thermal infrared ranges, the spectral reflectance of soil is directly measured using a spectrometer (Huang et al., 2018). Building upon this , through quantitative detection of HM elements in different types of soil under different environmental conditions, supplemented by physical and chemical characteristic data, the sensitive bands of HM elements in different types of soil are diagnosed and identified, and corresponding soil HM elements quantitative prediction models are analyzed. The function of HRS for direct monitoring of HM pollution is to transform HM elements in soil into soil organic matter and clay minerals. This process can be summarized as their adsorption onto carbonate minerals and iron manganese oxides.

3.1.2. Indirect monitoring of soil HMs pollution

This article aims to use hyperspectral technology to measure the reflectance spectra of crop canopies and leaves, and combine them with measured soil HM content. By analyzing the correlation between crop reflectance spectra and soil HM content, sensitive spectral bands can be selected and corresponding prediction models can be analyzed to achieve an indirect estimation of soil HM pollution levels. On a larger scale, the status of HM pollution on soil surfaces can be continuously monitored through remote sensing methods such as airplanes and artificial satellites in aviation and aerospace. Leveraging HRS technology, soil HM pollution can be indirectly monitored. Additionally, HMs can interfere with chlorophyll synthesis, resulting in changes in spectral information of leaves and canopies. Therefore, this project plans to use HRS technology to estimate soil HM pollution content through joint analysis of different spectral indicators.

3.2. Extraction of characteristic spectra

To achieve the correlation and related modeling between crop leaf hyperspectrum and research objectives (soil HMs, grain HMs), it is necessary to comprehensively extract and characterize hyperspectral information. The commonly used feature spectrum extraction methods include:

Single conversion processing: The spectral image can be smoothed and applied to the next conversion process to remove noise and improve the signal-to-noise ratio. The main conversion processes include the reciprocal, square root, and reciprocal logarithmic processes.

Derivative processing: In spectral analysis, derivative spectroscopy technology is a commonly used preprocessing method that can remove the influence of certain baselines and other background factors, thereby improving the resolution and sensitivity of the spectrum. It can also enhance the spectral information contained in hyperspectrum. Usually, first-order and second-order differentials are used.

Vegetation index is a simple and effective experiential method for measuring surface vegetation contour, typically designed using red visible light and near-infrared spectral channels (Keshavarzi and Kumar, 2019). In a sense, these indicators can better reflect the growth status, biomass, and health status of plants and can be used to diagnose a series of biochemical and biophysical indicators of plants. Compared to single-band diagnosis, the sensitivity is higher. The vegetation index varies according to the development stage: the first vegetation index is based on different spectral data, and it is mostly based on empirical remote sensing inversion. This vegetation index does not consider the atmosphere, soil physicochemical properties, and soil interaction. The second vegetation index is a type of vegetation index based on physics, mathematics, and logic, which comprehensively considers the effects of factors such as atmosphere, vegetation, soil, terrain, and electromagnetic radiation and continuously corrects the original vegetation index. This can establish a new, universal, scalable, and highly applicable vegetation index.

3.3. Issues in measuring HM content in soil and crops

There are three main problems in measuring HM content in soil and crops. Firstly, the accuracy of HRS data is relatively low and is constrained by various factors. For instance, when utilizing satellite remote sensing data for spectral analysis, significant errors in the spectral data may arise due to various factors such as atmospheric conditions and cloud cover. Hyperspectral images contain dozens to hundreds of bands, resulting in a lot of data redundancy. Improper processing can affect high spectral classification accuracy due to the high correlation between bands, necessitating increased training sample numbers for classification. Insufficient training samples often result in unreliable training parameters. Overall, the accuracy of hyperspectral remote sensing data is relatively low, primarily due to factors such as large data volume, inadequate training samples, and limitations of models and methods. Under current conditions, this error is difficult to avoid. With the expansion of the scope and scale of remote sensing monitoring, its influencing factors would become more complex and diverse, and the impact on soil spectral information would become more prominent (Zhao et al., 2022).

Secondly, achieving large-scale monitoring from ground-based propulsion to satellite remote sensing is challenging. Currently, HRS monitoring of HMs in soil remains at the “field sampling indoor analysis detection” stage, hindering rapid development from ground-based spectroscopy to satellite remote sensing. Although crop growth environment and growth monitoring largely rely on satellite remote sensing technology, acquiring satellite HRS data is challenging due to factors such as crop growth cycles, impeding large-scale real-time monitoring of HM pollution in soil and crops (Osman et al., 2021). Thirdly, existing quantitative models for HMs in soil and crop grains suffer from low computational accuracy. The quantitative model of soil HM pollution based on HRS technology still faces the problem of low prediction accuracy. On the one hand, due to the inherent errors of the model, the mutual influence between data cannot be completely eliminated. In addition, due to the small number of samples used for modeling and the poor representativeness of the data, the accuracy of the modeling results is low.

4. Collection and preprocessing of soil data

4.1. Collection and soil samples

The research area of this article is located at longitude 106°45′-109°7′ E and latitude 23°35′-25°57′ N. It exhibits characteristics of a subtropical monsoon climate, predominantly influenced by a maritime climate, featuring warm and humid conditions. Precipitation in this area is generally high, with an uneven distribution and a pronounced rainy season, mainly concentrated in summer. Meanwhile, there are also some seasonal droughts and floods in the region. Summer temperatures can soar above 30 °C, while winters are relatively cool but not severely cold,with temperatures typically around 10 °C. Specifically, summer maximum temperatures can exceed 30 °C, while winter minimum temperatures can drop below 0 °C.

The river in the area has a bottom bed width of 485 m, a water depth of 21 m, an average water level of 307 m, and a low water level of 8–9 m. The Youjiang River spans a total length of 707 km, with a drainage area of 38,600 km^2 and an average annual runoff of 17.2 billion m^3, making it an important river. The predominant soil types in this area are lime soil and paddy soil, and the main crops cultivated are corn and rice. Due to its unique geographical location, frequent tides occur, and seawater flows into arid areas through connected waterways, resulting in an increase in soil salinity and HM concentrations, posing great harm to agricultural production.

This study conducted field equidistant grid sampling from 2017 to 2020, with sample intervals controlled at around 500 m. The crops sampled included corn and rice, and the sampling sites included calcareous soil and paddy soil. This article investigated the contents of arsenic (mg/kg), cadmium (mg/kg), chromium (mg/kg), mercury (mg/kg), lead (mg/kg), copper (mg/kg), zinc (mg/kg), nickel (mg/kg), and selenium (mg/kg) in both soil and crops. HRS was used to calculate the pH value, organic matter content (g/kg), and cation exchange capacity (cmol(+)/kg) in the soil.

4.2. Preprocessing of soil spectral data

In order to effectively extract soil element information from hyperspectral data, it is necessary to preprocess the original reflection spectrum to eliminate background noise, enhance differences between similar spectra, and highlight spectral feature values. This article conducts image denoising, enhancement, and feature extraction on HRS images of soil in the survey area, as depicted in Figure. From the figure, it can be seen that the noise in the soil HRS image almost disappears after image denoising, which is very conducive to soil monitoring. Following image enhancement, the distribution contour of the image becomes clearer, and the boundaries of soil and crops become clearer after contrast enhancement, and the differences between similar spectra are also more pronounced. After image feature extraction, the spectral features of soil HRS images become more prominent.

5. Experiments to calculate HM content in soil and crops using HRS technology

5.1. HM content in soil and crops in 2017

This article analyzes the HM content in soil and crops based on the soil and crop data collected from HRS technology images in this experiment. In 2017, two sets of data were collected: one for crops and the other for soil. Both sets included calculations of HM content in soil and crops, thus facilitating analysis from two perspectives. Firstly, this article analyzes it from the perspective of crops, as displayed in Table 1. According to the data in Table 1, the average HM content in rice is 2.71 mg/kg, while in corn, it is 2.46 mg/kg. In paddy soil, the average HM content is 2.75 mg/kg, whereas in lime soil, it is 2.49 mg/kg. Among crops, zinc exhibits the highest HM content, while mercury has the lowest. Similarly, in soil, the HM content is still the highest in zinc and the lowest in mercury. Subsequently, this article analyzes the content of different types of HMs in soil samples collected in 2017 and investigates the soil's pH value, organic matter, and cation exchange capacity. The specific analysis is presented in Table 2. According to Table 2, the crops in the soil sampling grew in soil with a pH of around 6.196, whereas the overall soil pH was around 6.841. The organic matter content in the crop category is about 30.484 g/kg, and in the soil category, it is about 30.287 g/kg. Regarding cation exchange capacity, rice exhibits a higher value than corn, indicating a stronger fertilizer retention capacity of rice, while lime soil has a

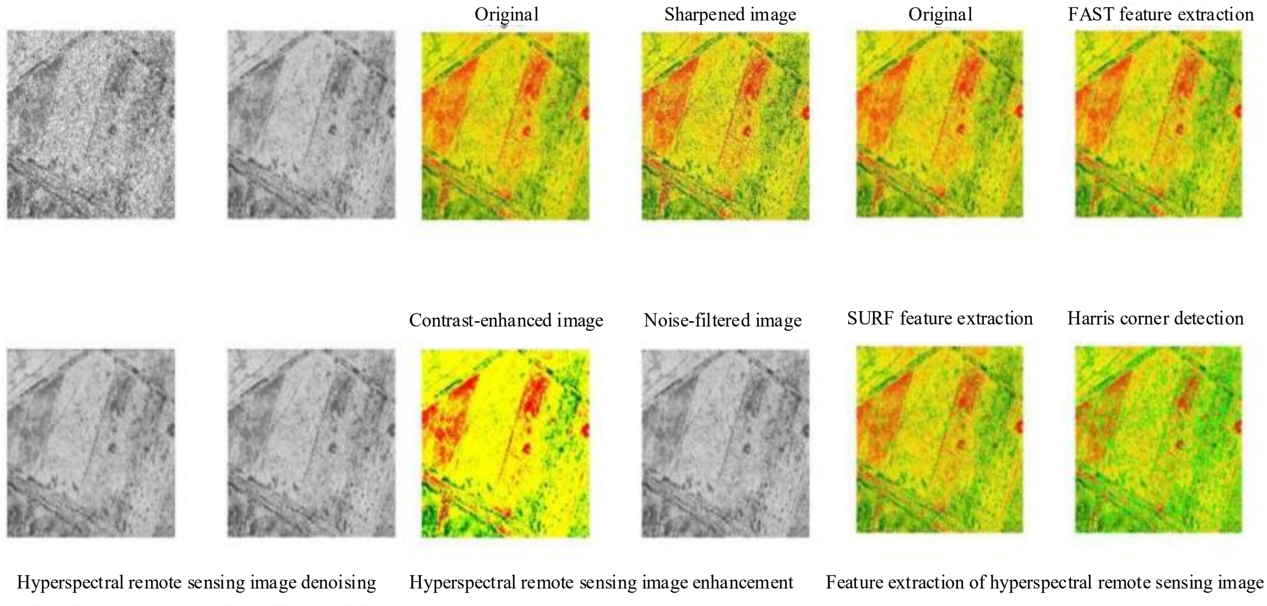

Figure. Preprocessing of soil HRS images.

Table 1. Analysis of HM content of different categories in crop sampling.

	Crops			Soil		
	Rice	Corn	Mean value	Paddy soil	Lime soil	Mean value
Average sampling area	0.830	1.310	1.070	0.855	0.650	0.753
Arsenic (mg/kg)	0.025	0.120	0.073	0.025	0.158	0.092
Cadmium (mg/kg)	0.252	0.028	0.140	0.249	0.068	0.158
Chromium (mg/kg)	0.060	0.037	0.049	0.060	0.036	0.048
Mercury (mg/kg)	0.011	0.003	0.007	0.012	0.003	0.007
Lead (mg/kg)	0.076	0.047	0.061	0.050	0.042	0.046
Copper (mg/kg)	2.600	1.807	2.204	2.666	1.846	2.256
Zinc (mg/kg)	20.900	19.920	20.410	21.254	20.007	20.630
Nickel (mg/kg)	0.360	0.138	0.249	0.352	0.166	0.259
Selenium (mg/kg)	0.110	0.060	0.085	0.119	0.078	0.099

Table 2. Analysis of HM content of different categories in soil sampling.

	Crops			Soil		
	Rice	Corn	Mean value	Paddy soil	Lime soil	Mean value
Total arsenic (mg/kg)	34.393	23.314	28.854	47.187	44.629	45.908
Cadmium (mg/kg)	1.237	0.992	1.114	1.325	1.626	1.476
Chromium (mg/kg)	54.922	92.565	73.743	54.060	198.735	126.398
Total mercury (mg/kg)	0.244	0.294	0.269	0.234	0.607	0.421
Lead (mg/kg)	57.203	47.933	52.568	57.262	76.035	66.649
Copper (mg/kg)	26.933	31.505	29.219	29.066	62.749	45.908
Zinc (mg/kg)	165.987	134.660	150.323	180.870	166.510	173.690
Nickel (mg/kg)	25.531	21.031	23.281	25.335	48.346	36.841
Total selenium (mg/kg)	0.627	0.499	0.563	0.634	0.284	0.459
pH value	6.469	5.923	6.196	6.387	7.295	6.841
Organic matter (g/kg)	35.990	24.978	30.484	35.251	25.322	30.287
Cation exchange capacity (cmol(+)/kg)	18.476	8.684	13.580	17.838	18.184	18.011

higher cation exchange capacity than rice soil, indicating a stronger fertilizer retention capacity of lime soil.

5.2. HM content in soil and crops in 2018

This article uses HRS images to collect soil and crop data for 2018 and analyzes the HM content of crops and soil in that year. The specific survey results are presented in Table 3. In 2018, the average sampling area for crops was 497.088 acres, while for soil, it was 495.100 acres. The mercury content in crops is recorded as 0.005 mg/kg, whereas the HM mercury content in soil has not been measured. Additionally, the content of inorganic arsenic in soil is 0.082 mg/kg higher than that in crops. The elevated content of inorganic arsenic can adversely affect the nutrient uptake of plants. It is not conducive to the growth of crops, and. Moreover, the presence of inorganic arsenic in crops can also pose health risks to humans.

5.3. HM content in crops in 2019

After examining the HM content of crops and soil in 2017 and 2018, this article also analyzed the monitored crop data for 2019. The specific results are presented in Table 4. According to Table 4, in the 2019 survey data, the zinc content of rice was approximately 18.872 mg/kg, indicating a decrease of 0.287 mg/kg compared to 2018. Similarly, the zinc content of corn is about 21.521 mg/kg, reflecting a decrease of 7.253 mg/kg compared to 2018. In both 2018 and 2019, the content of HM zinc in rice was lower than that in corn. Overall, the HM content of rice is 2.191 mg/kg, while that of corn is 2.389 mg/kg, representing a difference of 0.198 mg/kg.

5.4. HM content in soil and crops in 2020

Next, this article analyzes the HM content of soil and crops monitored in 2020, with the specific analysis results provided in Table 5. In the 2020 survey, the HM content in crops was approximately 2.760 mg/kg, with corn having a 0.493 mg/kg higher HM content than rice. Regarding soil, the HM content is 14.838 mg/kg, among which the HM content in paddy soil is 24.841 mg/kg lower than that in limestone soil. In 2020, the mercury content in paddy soil was recorded as 0.005 mg/kg. The mercury content of calcareous soil was measured at 41.357 mg/kg, significantly exceeding the standard limit. This indicates that it is not suitable to plant crops in the calcareous soil during that year, as the high HM content inhibits crop growth and poses a serious risk to physical health.

Table 3. Analysis of HM content in soil and crops in 2018.

	Crops			Soil		
	Rice	Corn	Mean value	Paddy soil	Lime soil	Mean value
Average sampling area	446.419	547.758	497.088	621.906	368.294	495.100
Chromium (mg/kg)	0.062	0.060	0.061	0.056	0.069	0.063
Cadmium (mg/kg)	0.183	0.029	0.106	0.146	0.019	0.083
Lead (mg/kg)	0.051	0.050	0.050	0.053	0.045	0.049
Mercury (mg/kg)	0.007	0.003	0.005	/	/	/
Total arsenic (mg/kg)	0.198	0.022	0.110	0.183	0.022	0.103
Inorganic arsenic (mg/kg)	0.208	0.000	0.104	0.204	0.167	0.186
Copper (mg/kg)	2.698	1.982	2.340	2.518	2.026	2.272
Zinc (mg/kg)	19.159	28.774	23.966	18.926	21.921	20.423
Nickel (mg/kg)	0.244	0.244	0.244	0.239	0.172	0.206
Selenium (mg/kg)	0.074	0.054	0.064	0.066	0.069	0.068

Table 4. Analysis of HM content in crops in 2019.

	Crops		
	Rice	Corn	Mean value
Cadmium (mg/kg)	0.139	0.038	0.088
Mercury (mg/kg)	0.005	0.002	0.004
Arsenic (mg/kg)	0.254	0.024	0.139
Inorganic arsenic (mg/kg)	0.245	0.382	0.314
Lead (mg/kg)	0.040	0.031	0.036
Chromium (mg/kg)	0.049	0.034	0.042
Copper (mg/kg)	2.058	1.646	1.852
Zinc (mg/kg)	18.872	21.521	20.196
Nickel (mg/kg)	0.181	0.143	0.162
Selenium (mg/kg)	0.070	0.069	0.070

Table 5. Analysis of HM content in soil and crops in 2020.

	Crops			Soil		
	Rice	Corn	Mean value	Paddy soil	Lime soil	Mean value
Cadmium (mg/kg)	0.107	0.012	0.059	0.120	33.539	16.829
Total mercury (mg/kg)	0.005	0.006	0.006	0.005	41.357	20.681
Total arsenic (mg/kg)	0.177	0.017	0.097	0.184	37.465	18.825
Lead (mg/kg)	0.036	0.039	0.038	0.037	46.029	23.033
Chromium (mg/kg)	0.109	0.093	0.101	0.116	28.080	14.098
Copper (mg/kg)	2.154	2.004	2.079	2.129	37.489	19.809
Zinc (mg/kg)	19.603	24.446	22.025	18.714	20.921	19.817
Nickel (mg/kg)	0.371	0.375	0.373	0.390	0.378	0.384
Selenium (mg/kg)	0.065	0.070	0.067	0.059	0.064	0.062

5.5. Comparative analysis of HM content in soil and crops using HRS technology

HMs may persist in soil for a long time, seriously affecting soil quality. The coexistence of different HM pollutants may lead to biological toxicity and alter microbial activity (Xu et al., 2021). In order to study the calculation effect of HM content in soil and crops using HRS technology from 2017 to 2020, this paper conducted a comparative analysis of HM content and enrichment coefficient using neural network algorithms.

To achieve the mapping of input vectors to hidden layers, neural network functions are usually used as their "basis" to form a hidden layer space. When the center of the neural network is determined, its corresponding relationship is determined. Due to the linear transformation between the hidden layer and the output layer in the network, the input and output of the network are a simple linear addition of the hidden layer outputs, with the sum of their weights. Meanwhile, the excitation function of the model is a new radial basis function. The radial basis function is a real-valued function whose value is only dependent on the distance from the origin, namely Φ(x) = Φ(IxI),or can also be a distance to any point c, where point c becomes the center point, or Φ(x,c) = Φ(Ix-cI). Any function Φ that satisfies the characteristic of Φ(x)=Φ(IxI) is called a radial vector function, and the standard generally uses Euclidean distance, although other distance functions are also possible. The basis function has the property of local response to the input signal, and the output of the model increases with the distance from the central region of the basis function, thus giving a local approximation of the neural network. The basis function has a characteristic of local response to the input signal, and the output of the model increases with the increase of the distance from the center region of the basis function, thus giving the neural network local approximation. Firstly, the Gaussian radial basis function for calculating HM content is:

$$A(x) = exp\left[-\frac{1}{2}(\frac{x-p_k}{q_k})^2\right], k = 1,2,\cdots,n \quad (1)$$

In the formula, x is the activation factor of HM content, p_k, q_k are the center vector of the activation function and the width of the radial basis function, respectively. According to the radial basis function, the linear network output function for calculating HM content can be calculated as:

$$\mathrm{f}(x) = \sum_{k=1}^{n} r_k\, A(x), k = 1,2,\cdots,n \quad (2)$$

r_k is the implicit output value of the output layer. Then, based on the network output function, the variance formula for HM calculation under the radial basis function is determined as follows:

$$q_i = \frac{p_{max}}{\sqrt{2h}}, i = 1,2,\cdots,n \quad (3)$$

In the formula, h is the grouped Euclidean distance of the radial basis function, and p_{max} is the maximum center vector of the radial basis function. The final weight between the calculated and actual values of HM content can be obtained as follows:

$$R = exp\left(\frac{h}{p_{max}^2}||x_j - o_j||\right), j == 1,2,\cdots,n \quad (4)$$

Among them, x_j is the calculated value of HM content, and o_j is the actual value of HM content. The enrichment coefficient of HM content can be analyzed through normalization based on the weight values.

$$\bar{S} = \frac{x_j - x_{min}}{x_{max} - x_{min}} \quad (5)$$

Among them, x_{max}, represent the maximum and minimum values calculated for HM content. Based on the survey data from 2017 to 2020, the enrichment coefficients were analyzed, and the specific analysis results are presented in Table 6.

According to Table 6, the HM contents of crops from 2017 to 2020 are 2.586, 2.705, 2.290, and 2.760, respectively. The soil HM contents in 2017, 2018, and 2020

Table 6. Comparative analysis of HM content in soil and crops using HRS technology.

	2017	2018	2019	2020	Mean value
Heavy metals in rice (mg/kg)	2.710	2.288	2.191	2.514	2.426
Heavy metals in corn (mg/kg)	2.462	3.122	2.389	3.007	2.745
Heavy metals in crops (mg/kg)	2.586	2.705	2.290	2.760	2.586
Heavy metals in paddy soil (mg/kg)	2.754	2.239	/	2.417	2.470
Lime soil HMs (mg/kg)	2.489	2.451	/	27.258	10.733
Heavy metals in soil (mg/kg)	2.622	2.345	/	14.838	4.951
Concentration factor	0.987	1.154	/	0.186	0.582

are 2.622, 2.345, and 14.838, respectively. Employing the formula for calculating the enrichment coefficient, the HM enrichment coefficients for 2017, 2018, and 2020 were determined to be 0.987, 1.154, and 0.186, respectively. It can be seen that the HM enrichment coefficient in 2020 was the smallest, whereas it peaked in in 2018 was the highest. Through the above experimental analysis, it was found that zinc content is highest in soil and crops, while mercury content is lowest. HRS technology can be used to monitor the HM content of soil and crops. By reducing the HM content in the soil, the growth speed of crops can be improved, and the HM content in crops can be reduced, reducing the harm to human health.

6. Conclusions

By using ground HRS technology, hyperspectral data of surface targets can be directly obtained, with the characteristics of high resolution and continuity. Real-time detection of hyperspectral data of the tested object can be achieved without damaging soil and crops. This can thus overcome the drawbacks of traditional HM detection methods, such as cumbersome steps, easy damage to the tested object, and difficulty in real-time detection. The research results of this project would provide strong data support for the accurate acquisition and monitoring of soil spectral information, and also lay a foundation for the application of soil spectral information. This article used ground HRS data for monitoring changes in HM content in soil and crops, but failed to utilize large-scale HRS technologies such as airplanes and drones. For three-dimensional multi-scale monitoring, future research should focus on combining ground HRS with high-altitude HRS, and even satellite remote sensing to achieve large-scale multiscale remote sensing monitoring of metal content changes. Despite its powerful information acquisition capabilities, hyperspectral remote sensing technology still faces limitations in handling heavy metal content and agricultural potential. For example, for some heavy metal elements, the spectral information may be relatively weak, and it is difficult to be accurately detected and identified. In the process of hyperspectral remote sensing image processing, it is usually necessary to exclude the influence of light, temperature, moisture, and organic matter, which increases the complexity and difficulty of processing. Therefore, the research on heavy metal content and agricultural potential based on hyperspectral remote sensing image processing still needs to be further improved and perfected.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Data availability statement

The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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