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Hyperspectral Technology in Agricultural Soil Heavy Metal Detection: Current Applications and Future Directions

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Abstract: Soil heavy metal pollution has become a global environmental issue, posing serious threats to agricultural productivity, food safety, and human health. The emergence of hyperspectral technology provides new approaches for rapid and non-destructive detection of soil heavy metals. This paper reviews the application of hyperspectral technology in identifying heavy metal elements in agricultural soils. First, it introduces the fundamental principles of hyperspectral technology, including the relationship between soil spectral characteristics and heavy metal elements, hyperspectral data acquisition and processing, as well as spectral feature extraction and analysis methods. Then, the research progress in agricultural soil heavy metal identification using hyperspectral technology is detailed from three aspects: laboratory studies, field applications, and integrated applications with other technologies. Studies demonstrate that hyperspectral technology can achieve high-precision prediction of soil heavy metal content through interactions between soil components and heavy metals, utilizing methods such as Continuous Wavelet Transform (CWT) combined with Radial Basis Function (RBF) models. However, practical applications still face challenges including soil background interference, data complexity, and high operational costs. Finally, the paper discusses the advantages and limitations of hyperspectral technology in agricultural soil heavy metal identification, and prospects future development directions including technological improvements and innovations, expansion of application scopes, and establishment of standardization and normalization. Future research should focus on enhancing sensor resolution, optimizing algorithms, and establishing unified spectral databases to improve model generalizability, while promoting widespread application of hyperspectral technology in agricultural soil heavy metal monitoring through multidisciplinary collaboration.

Keywords: Soil heavy metal pollution; Hyperspectral technology; Agricultural soil; Heavy metal element identification; Spectral feature extraction.

1. Introduction

Soil heavy metal pollution has become a critical global environmental issue, posing severe threats to agricultural productivity, food safety, and human health. Heavy metals such as cadmium (Cd), lead (Pb), and nickel (Ni) accumulate in soils through industrial activities, mining, and improper waste disposal, leading to reduced crop yields, compromised agricultural product quality, and long-term health risks through the food chain (Zhang et al., 2015; Chen et al., 2018). In China, approximately 19.4% of agricultural soils are contaminated by heavy metals (Figure 1), with Cd being the most prevalent pollutant, highlighting the urgency for effective monitoring and remediation strategies (Zhang et al., 2015; Wang et al., 2018).

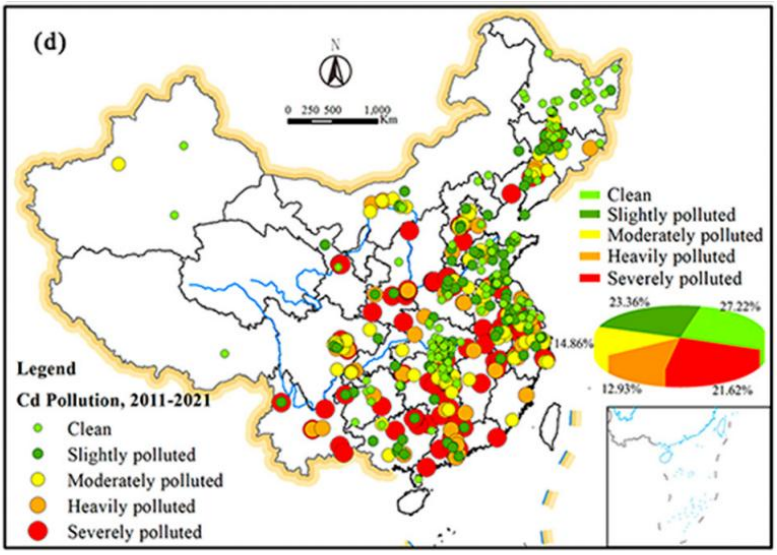

Figure 1. The geographical locations of Cd in the agricultural soil of China, with the dot size representing metal concentrations (Wang et al., 2023)

The emergence of hyperspectral technology offers a transformative approach for rapid and non-destructive detection of soil contaminants. Hyperspectral imaging captures detailed spectral signatures across a wide wavelength range (350–2500 nm), enabling the identification of subtle spectral variations caused by heavy metal interactions with soil components (Wu et al., 2005a; Xie et al., 2007). For instance, studies have demonstrated that spectral transformations, such as first and second derivatives, enhance the correlation between spectral data and heavy metal concentrations, improving model accuracy for elements like Ni and Cd (Zhang et al., 2019; Tan et al., 2021). Hyperspectral sensors, including ground-based spectrometers (e.g., ASD FieldSpec4) and airborne systems, have been widely deployed to collect soil reflectance data, which, when combined with machine learning algorithms like partial least squares regression (PLSR) and radial basis function neural networks (RBF), enable quantitative inversion of heavy metal contents (Wang et al., 2018; Zhang et al., 2022).

Laboratory studies have validated the efficacy of hyperspectral technology in identifying heavy metals under controlled conditions. For example, Zhang et al. (2019) achieved high precision (R^2 = 0.83) in predicting soil Cd content using continuous wavelet transform (CWT) combined with RBF models. However, field applications face challenges such as environmental interference (e.g., soil moisture, organic matter) and data complexity, necessitating advanced preprocessing and modeling techniques (Wang et al., 2018; Fu et al., 2013). Integrating hyperspectral data with geospatial technologies like GIS further enhances spatial-temporal monitoring capabilities, providing a holistic framework for pollution management (Zhong et al., 2023; Guan et al., 2019).

Despite its advantages—non-destructive detection, rapid large-area coverage, and multi-element monitoring—hyperspectral technology remains constrained by high costs, technical complexity, and dependence on soil background conditions (Wang et al., 2018; Zhang et al., 2022). Future advancements require improved sensor resolution, optimized algorithms (e.g., ensemble learning frameworks), and standardized protocols to bridge laboratory research and practical field applications (Tan et al., 2021; Tan et al., 2021). This study emphasizes the pivotal role of hyperspectral technology in agricultural soil monitoring and aims to provide a technical foundation for sustainable soil management.

2. Principles of Hyperspectral Technology in Identifying Heavy Metal Elements

2.1. Relationship Between Soil Spectral Characteristics and Heavy Metal Elements

The interaction between heavy metals and soil spectral reflectance forms the theoretical basis for hyperspectral detection. Heavy metals indirectly alter soil spectral characteristics by influencing soil components such as organic matter, iron oxides, and clay minerals (Wu et al., 2007; Stenberg, 2010). For instance, cadmium (Cd) and lead (Pb) tend to form complexes with organic matter, while arsenic (As) and chromium (Cr) are often adsorbed by iron oxides, modifying their spectral absorption features (Kooistra et al., 2001; Xia et al., 2015). Studies have shown that soil spectral reflectance generally exhibits a negative correlation with heavy metal concentrations. For example, Zhang et al. (2019) observed that Cd concentrations were strongly negatively correlated with reflectance at wavelengths of 968 nm after continuum removal transformation, with correlation coefficients reaching 0.497. Similarly, spectral second derivatives significantly enhanced the correlation between Ni content and reflectance, achieving a maximum correlation coefficient of -0.512 (Zhang et al., 2019).

The spectral response mechanisms of heavy metals vary depending on their chemical properties and binding states. For example, Hg exhibits weak direct spectral absorption but shows enhanced detectability after mathematical transformations such as logarithmic reciprocal first derivatives (Wang et al., 2018). Hyperspectral technology captures subtle changes in soil reflectance caused by heavy metal accumulation, enabling qualitative and quantitative analysis through characteristic absorption peaks and spectral curve morphology (Wu et al., 2005b; Yuan et al., 2020).

2.2. Acquisition and Processing of Hyperspectral Data

Hyperspectral data acquisition relies on sensors covering the visible to near-infrared (VNIR, 350–1,000 nm) and short-wave infrared (SWIR, 1,000–2,500 nm) ranges. Common instruments include field spectrometers (e.g., ASD FieldSpec) and airborne sensors (e.g., HyMAP) (Figure 2). Laboratory measurements typically use halogen lamps to eliminate ambient light interference, with each sample scanned 5–20 times to obtain averaged reflectance curves (Zhang et al., 2019; Tan et al., 2021).

Data preprocessing is critical for improving signal-to-noise ratios. Key steps include:

Radiometric correction: $R = \frac{I-B}{W-B}$

Where R, I, B, and W represent corrected, raw, dark current, and white reference spectra, respectively.

Spectral smoothing: Techniques like Savitzky-Golay (SG) filtering reduce high-frequency noise (Fu et al., 2013).

Mathematical transformations: First derivatives (FD), second derivatives (SD), and continuum removal (CR) enhance spectral features and mitigate baseline drift (Zhang et al., 2019). For example, SD transformation improved the prediction accuracy of Cd by 15% compared to raw spectra in mining area soils (Zhang et al., 2019).

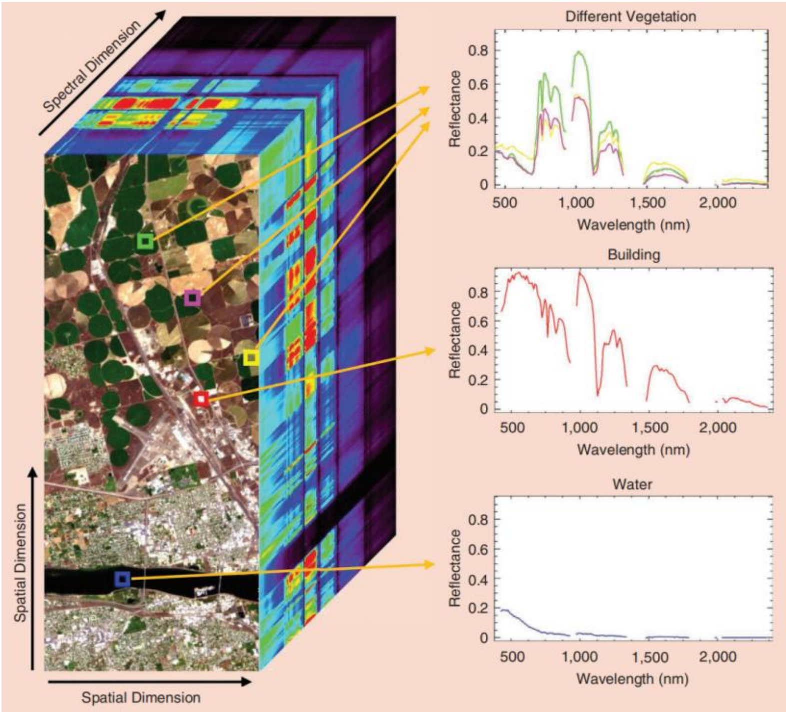

Figure 2. An example of an HS image cube for an agricultural area and the pixel spectral signatures associated with different land-cover materials (Liu et al., 2019).

2.3. Spectral Feature Extraction and Analysis Methods

Feature extraction aims to identify wavelengths sensitive to specific heavy metals. Common methods include:

Correlation analysis | r |>0.6 (Zhang et al., 2019).

Successive Projections Algorithm (SPA): Reduces multicollinearity by iteratively selecting minimally redundant wavelengths (Meng et al., 2020).

Wavelet transform: Extracts multiscale spectral features, particularly effective for detecting weak heavy metal signals (Zhang et al., 2019).

Quantitative models establish relationships between spectral features and heavy metal concentrations:

Linear modelsR^2>0.7 for Cd and as prediction (Zhang et al., 2019).

Nonlinear machine learning models: Radial basis function neural networks (RBF) outperform PLSR in complex scenarios. Zhang et al. (2019) reported that the CWT-RBF model reduced RMSE by 30% compared to PLSR for Cd prediction.

Hybrid approaches: Combining spectral indices with environmental factors (e.g., topography, soil moisture) improves prediction accuracy (Cai et al., 2022; Song et al., 2019).

3. Application Progress of Hyperspectral Technology in Agricultural Soil Heavy Metal Element Identification

3.1. Laboratory Research

Hyperspectral technology has demonstrated significant potential in laboratory $R^2 > 0.8$) for Cd and Pb. Similarly, Guo et al. (2021) explored the feasibility of hyperspectral inversion for nickel (Ni) content in iron mine soils, finding that spectral derivative transformations (e.g., second derivative) significantly enhanced the correlation between spectral data and Ni concentrations, with the $SDR^2 = 0.842$ and RMSE = 4.474.

However, laboratory studies face limitations, such as the dependency on homogeneous soil samples and the exclusion of environmental variables. For example, spectral interference from soil organic matter (SOM) and moisture content often complicates direct heavy metal detection, necessitating advanced preprocessing techniques like multiplicative scatter correction (MSC) and Savitzky-Golay smoothing to mitigate noise (Wang et al., 2019).

3.2. Field Applications

Field applications of hyperspectral technology face challenges due to environmental variability but have shown promising results in large $R^2 = 0.73$) despite field noise.

Challenges persist, including spectral interference from vegetation cover, soil moisture fluctuations, and heterogeneous soil textures. Zhou et al. (2015) highlighted that environmental factors could reduce model accuracy by 15–20% in field settings compared to laboratory conditions. To address this, studies have employed spatial-spectral feature fusion and machine learning algorithms like random forest (RF) to improve robustness.

3.3. Integrated Applications with Other Technologies

The integration of hyperspectral technology with complementary methods enhances its practicality in agricultural soil monitoring. For example, Zhang et al. (2019) combined hyperspectral imaging with XRF to achieve rapid, multi-element detection, leveraging XRF's high precision for calibration. Similarly, Chen et al. (2022) integrated hyperspectral data with geographic information systems (GIS) to map spatial distributions of heavy metals, enabling targeted remediation strategies.

Emerging trends include coupling hyperspectral sensors with unmanned aerial vehicles (UAVs) for high-resolution spatial mapping. Wang et al. (2019) reviewed UAV-based hyperspectral systems for crop health and soil contamination monitoring, noting their efficiency in covering large agricultural areas. Additionally, machine learning frameworks like deep forest (DF21) have been applied to hyperspectral data, with Zhang et al. (2023) reporting a 12% improvement in Cd prediction accuracy compared to traditional PLSR models.

Despite these advancements, challenges remain in standardizing data acquisition protocols and reducing computational complexity. Future integration with artificial intelligence (AI) and IoT platforms may further streamline data processing and real-time monitoring (Gao et al., 2023).

4. Advantages and Limitations of Hyperspectral Technology in Agricultural Soil Heavy Metal Identification

4.1. Advantages

Hyperspectral technology has emerged as a transformative tool for agricultural soil heavy metal identification due to its non-destructive nature, rapid detection capabilities, and multi-element monitoring potential. Unlike traditional chemical analysis methods that require extensive laboratory processing and destructive sampling (Kemper & Sommer, 2002), hyperspectral imaging enables in-situ, non-invasive detection of soil properties, preserving soil integrity and minimizing environmental disturbance (Wang et al., 2018). This feature is particularly advantageous for long-term monitoring of agricultural soils, as repeated sampling can be conducted without degrading soil quality.

The high efficiency of hyperspectral technology allows for rapid acquisition of large-scale soil data. For instance, Shi et al. (2014) demonstrated that hyperspectral models could delineate heavy metal contamination risk zones in agricultural fields within hours, compared to weeks required for conventional geochemical analysis. This efficiency is further enhanced by the ability to simultaneously monitor multiple heavy metals (e.g., Cd, Hg, As) using a single dataset (Zhao et al., 2018; Zhang et al., 2019). By leveraging spectral signatures unique to different elements, hyperspectral systems reduce the need for separate analytical procedures, streamlining pollution assessment workflows.

Recent advancements in spectral transformation and machine learning integration have significantly improved prediction accuracy. For example, Zhang et al. (2019) reported that combining continuous wavelet transform (CWT) with radial basis function neural networks (RBF) achieved an R^2 of 0.91 for as content prediction in reclaimed soils. Similarly, Zhao et al. (2018) highlighted that integrating hyperspectral data with geostatistical methods enhanced the precision of Hg quantification, with RMSE reductions of 36%. These innovations underscore hyperspectral technology's adaptability to diverse agricultural environments.

4.2. Limitations

Despite its advantages, hyperspectral technology faces challenges related to soil background interference, data complexity, and operational costs. Soil properties such as organic matter content, moisture, and texture significantly influence spectral reflectance, often masking subtle heavy metal signals (Wang et al., 2018; Zhang et al., 2019). For instance, Shi et al. (2014) noted that high clay content in soils attenuated spectral absorption features of Cd, leading to model inaccuracies. Such dependencies necessitate region-specific calibration, limiting the generalizability of hyperspectral models across heterogeneous agricultural landscapes.

The complexity of hyperspectral data poses another barrier. With hundreds of narrow spectral bands, preprocessing steps (e.g., noise reduction, spectral smoothing, and feature selection) are computationally intensive. While algorithms like Continuous Wavelet Transform (CWT) and Boruta feature selection have improved feature extraction (Zhang et al., 2019; Zhao et al., 2018), their implementation requires specialized expertise, raising the technical threshold for agricultural practitioners (Wang et al., 2018). Furthermore, the high cost of hyperspectral sensors and data processing infrastructure restricts widespread adoption, particularly in resource-limited regions (Zhang et al., 2019).

4.3. Future Directions

Addressing these limitations requires algorithm optimization and cross-disciplinary collaboration. Developing hybrid models that integrate hyperspectral data with soil physicochemical parameters (e.g., pH, organic carbon) could mitigate background interference. Additionally, advancements in portable hyperspectral devices and cloud-based processing platforms may reduce costs and democratize access (Wang et al., 2018).

5. Future Development Directions of Hyperspectral Technology in Agricultural Soil Heavy Metal Element Identification

5.1. Technological Improvements and Innovations

The advancement of hyperspectral sensors is critical for enhancing detection accuracy. Current hyperspectral sensors face limitations in spectral resolution and signal-to-noise ratio when identifying trace heavy metals in complex soil matrices (Chen et al., 2022). Future sensors should expand spectral coverage to include the ultraviolet and thermal infrared ranges while improving spectral resolution to capture subtle absorption features of heavy metals like Cd and as (Zhang et al., 2019). Additionally, optimizing data processing algorithms is essential. Machine learning models such as stacked generalization frameworks (Liu et al., 2019) and deep forest architectures (Zhang et al., 2022) have demonstrated superior performance over traditional methods like partial least squares regression (PLSR), but require further refinement to handle hyperspectral data redundancy and nonlinear relationships. Integrating wavelet transforms with radial basis function neural networks (CWT-RBF) has shown promise in improving prediction accuracy for mining wasteland soils (Zhang et al., 2019), suggesting similar potential for agricultural systems.

5.2. Application Expansion

Hyperspectral technology must adapt to diverse agricultural ecosystems. Current studies predominantly focus on specific regions, such as iron mining areas (Shen et al., 2019) or wastewater-irrigated farmlands (Chen et al., 2015), limiting model generalizability. Future applications should address variability in soil types, moisture levels, and organic matter content across agroecosystems. For instance, combining hyperspectral data with geographic information systems (GIS) and X-ray fluorescence (XRF) could enhance spatial mapping precision in paddy fields and dryland farms (Chen et al., 2021). Furthermore, integrating hyperspectral systems with IoT-enabled unmanned aerial vehicles (UAVs) and edge computing devices will enable real-time, large-scale monitoring (Chen et al., 2022). Such integration aligns with precision agriculture needs, providing actionable insights for site-specific soil remediation.

5.3. Standardization and Regulation

Establishing standardized protocols is imperative to address inconsistencies in soil spectral data acquisition. Variations in preprocessing methods (e.g., drying, grinding) and environmental conditions (e.g., illumination, humidity) significantly impact spectral reproducibility (Shi et al., 2016). A unified framework for soil sample preparation, spectral measurement, and data calibration must be developed, drawing from existing laboratory protocols (Zhang et al., 2019). Concurrently, building open-access hyperspectral databases for agricultural soils will facilitate model validation and knowledge sharing. Initiatives like the soil spectral library for China's reclaimed mining areas (Zhang et al., 2019) exemplify this approach. Regulatory guidelines should also be formulated to govern technology deployment, ensuring data quality and interoperability across platforms.

6. Conclusion

Hyperspectral technology has demonstrated significant potential in identifying heavy metal elements in agricultural soils, offering a transformative approach to soil pollution monitoring and management. Current research highlights the capability of hyperspectral data to establish quantitative relationships between spectral features and heavy metal concentrations through advanced mathematical transformations and modeling methods. For instance, Guo et al. (2021) confirmed that spectral second-derivative transformation combined with multivariate linear regression (SD-MLR) achieved high stability and accuracy ($R^2 = 0.842$) in predicting nickel content in iron-mining areas, underscoring the effectiveness of spectral preprocessing in enhancing correlations between soil properties and heavy metals. Similarly, Chen et al. (2022) validated the superiority of machine learning models like partial least squares regression (PLSR) and support vector machines (SVM) in mapping multi-element contamination, which aligns with findings from Kooistra et al. (2001) on the feasibility of reflectance spectroscopy for Cd and Zn detection.

The non-destructive, rapid, and large-scale monitoring advantages of hyperspectral technology make it indispensable for agricultural soil health assessment (Gao et al., 2025). Laboratory studies have established robust spectral libraries and inversion models for specific heavy metals, such as Cd and As, by leveraging their indirect correlations with organic matter and iron oxides (Xu et al., 2011; Chen et al., 2015). However, challenges persist in field applications due to environmental variability, soil heterogeneity, and the complexity of hyperspectral data processing (Shen et al., 2019; Wang et al., 2019). Integration with GIS and IoT technologies has improved spatial analysis and real-time monitoring capabilities, yet standardization of protocols and cost reduction remain critical for widespread adoption (Lei et al., 2018; Liu et al., 2019).

Future advancements should focus on enhancing sensor resolution, optimizing algorithms (e.g., deep learning and random forest models), and establishing unified spectral databases to improve model generalizability (Zhou et al., 2021; Liu et al., 2023). Collaborative efforts to standardize hyperspectral workflows and reduce technical barriers will further solidify its role in sustainable

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