Atomic Spectroscopy

Review

Advances in Spectral Imaging for Heavy Metal Non-destructive Detection in Crops

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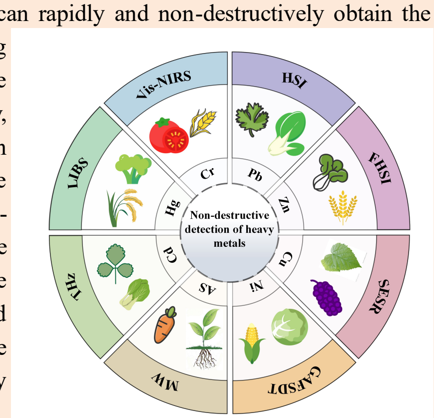
Received: *December 06, 2025;* ***Revised:*** *January 09, 2026;* ***Accepted:*** *January 29, 2026;* ***Available online:*** *January 29, 2026.*

DOI: 10.46770/AS.2025.262

ABSTRACT: Given the increasingly serious threat of heavy metal pollution in farmland to the safety of agricultural products and human health, it is of great significance to develop rapid, non-destructive detection technologies. Traditional chemical detection methods suffer from being destructive, time-consuming and costly. In contrast, spectrum and imaging technology has become the research hotspot due to its advantages of fast and non-destructive. Heavy metal pollution alters the physiological and biochemical characteristics and optical responses of crops. Spectrum and imaging technology can rapidly and non-destructively obtain the corresponding spectral and spatial information, providing a way for pollution screening and quantitative and qualitative analysis. This paper systematically reviews the application of spectral imaging techniques such as visible/near-infrared spectroscopy, hyperspectral imaging, fluorescence hyperspectral imaging, laser-induced breakdown spectroscopy, and Raman spectroscopy in this field, and identifies that these technologies existing limitations and challenges. Future research should focus on multi-technology integration, model universality improvement, and portable device development. Through algorithm optimization, cost control and the extension of the industrial chain, the in-depth application of spectrum and imaging technology should be promoted. This article aims to provide theoretical references and practical guidance for the research and application of rapid non-destructive detection technology for heavy metals in crops.



INTRODUCTION

Heavy metal contamination in agricultural products is a major challenge currently faced globally. With the continuous improvement of the living standards of global residents, the consumption pattern of agricultural products is accelerating its transformation from survivation-oriented to nutritious, healthy and high-quality.[1] This transformation has led the international community to put forward higher requirements for the supervision of the quality and safety of agricultural products.[2] Against this backdrop, the Food and Agriculture Organization of the United Nations (FAO) and the World Health Organization (WHO) have continuously emphasized in the "One Health" initiative that attention must be paid to the migration and accumulation of pollutants in the food chain, and have called for "the establishment of a more agile and transparent food safety monitoring system to address chemical risks including heavy metals".[3] A report by the World Bank further points out that the governance of heavy metal pollution in cultivated land is a key link in ensuring global food security, especially in maintaining the livelihoods of small-scale farmers in developing countries.[5] The above-mentioned international consensus and actions highlight the global high regard for the safety of cultivated land and the quality of agricultural products, and have promoted the research and application of rapid non-destructive detection technologies for heavy metals in crops.[6]

In agricultural production, crops often encounter soil fertility degradation, pollution and various adverse stresses, which lead to a significant decline in yield and quality. Among them, heavy metal pollution, due to its concealment, accumulation and irreversibility, has become a key factor affecting the quality and safety of agricultural products.[6] Globally, elements such as cadmium (Cd), lead (Pb), and arsenic (As) are the types of heavy metals with the widest distribution of pollution and the most significant toxic effects.[7] Such pollutants accumulate continuously in the soil-crop system, which can cause a series of toxic effects such as metabolic disorders and growth and development inhibition, and are not easily detectable in the early stage of pollution. Once visible symptoms appear, they often cause irreversible ecological and health risks, making governance extremely difficult,[8] and pose a continuous and serious threat to global food security production and human health.

Currently, conventional methods for detecting heavy metals in crops include atomic fluorescence spectrometry (AFS),[9] inductively coupled plasma mass spectrometry (ICP-MS),[10] and atomic absorption spectrometry (AAS),[11] among others. Although these methods have relatively high detection accuracy, they have inherent limitations such as complex sample pretreatment, sample damage, and expensive instruments and equipment,[12] making it difficult to meet the demands of large-scale and high-throughput safety screening and real-time monitoring of agricultural products. Therefore, the development of rapid, accurate and non-destructive heavy metal detection technologies has become an urgent need in the current international agricultural quality and safety field.

In recent years, non-destructive detection methods based on spectroscopy and imaging technologies have demonstrated broad prospects for detecting heavy metal stress in crops, owing to their advantages of rapidity, non-invasiveness, and in-situ applicability. These techniques enable the indirect quantitative assessment of contamination levels by capturing changes in crop physiological and biochemical parameters as well as phenotypic characteristics under heavy metal stress.[13-15] However, while advanced spectroscopic methods such as visible-near infrared spectroscopy (Vis-NIRS),[16] hyperspectral imaging technology (HSI),[17] laser-induced breakdown spectroscopy (LIBS),[18] and Raman spectroscopy (RS)[19] provide rich multidimensional spectral and spatial information, their raw data often contain significant noise and high-dimensional redundant variables unrelated to heavy metal content. Consequently, efficient data processing and modeling methods are essential to optimize and interpret spectral information, enabling the accurate extraction of features relevant to heavy metal concentration and stress intensity. Machine learning and deep learning algorithms not only enhance the analytical accuracy and model generalizability of spectral data,[20,21] but also, through their deep integration with spectroscopic imaging technologies, provide robust technical support for agricultural product quality and safety.

METHODOLOGY

This review followed a systematic methodology to collect and analyze studies on spectroscopic and imaging techniques for heavy metal detection in crops. Literature searches were performed in Web of Science and Engineering Village from 2005 to 2025, with supplementary searches in CNKI for Chinese-language publications. Search queries combined terms for analytical techniques (“Vis-NIRS”, “HSI”, “FHSI”, “LIBS”, “SERS”), heavy metals (“Cd”, “Pb”, “Hg”, “Cu”, “Cr”, “As”), and crop types (“rice”, “wheat”, “lettuce”).

After duplicate removal and title/abstract screening of over 2,000 records, 713 full-text articles were evaluated. Studies were excluded if they focused solely on soil or water rather than crop samples, lacked quantitative performance data (*e.g.*, detection limits, R^2, RMSEP), or were not directly relevant to crop heavy metal detection. Ultimately, 97 studies met all inclusion criteria and were retained for systematic analysis.

A standardized data-extraction form was used to capture technique specifications, sample information, target heavy metals, modeling methods, and key performance indicators—including linear ranges, precision, and advantages or limitations.

The extracted data were organized into technology-specific summary tables (Tables S1-S6) and further synthesized into a comparative overview table (Table 1) that contrasts the principles, strengths, limitations, typical detection limits, approximate cost levels, and analysis speeds of each technique. This systematic methodology establishes a rigorous, traceable basis for the comparative evaluation of spectroscopic and imaging techniques that follows.

Visible-near infrared spectroscopy

Visible-near infrared spectroscopy (Vis-NIRS) is a rapid and non-destructive analysis technique based on the vibrational energy level transitions of molecules.[23] The physical basis lies in that when light with wavelengths within the range of 400-2500 nm irradiates the sample, the hydrogen-containing functional groups in the organic molecules of the sample (*e.g.*, C–H, O–H, and N–H bonds) will undergo non-harmonic vibrations, resulting in frequency doubling and combined absorption of light of specific wavelengths.[24] By collecting these characteristic absorption signals, the detector can obtain a characteristic spectrum that contains information on the chemical composition, molecular structure and physical properties of the sample.

In the detection of heavy metals in crops, this technology captures with high sensitivity the physiological and biochemical responses of crops caused by heavy metal stress, including cell structure damage, changes in the content of chlorophyll and other pigments, obstruction of protein synthesis, abnormal water metabolism, *etc*.[25] It then establishes correlation models between these responses and heavy metal concentrations. Thus, the quantitative

Table 1. Comparative summary of spectroscopic and imaging techniques for heavy metal detection in crops

Techniques	Principle	Advantages	Limitations	LOD	Cost	Detection Speed
Vis-NIRS	Molecular overtone and combination vibrations of C–H, O–H, N–H bonds; indirect detection via plant physiological changes	Non-destructive, rapid, portable devices available, suitable for field use	Indirect; model-dependent; environmentally sensitive; low trace sensitivity	0.002–1 mg/kg	Low to Medium	Seconds to minutes
HIS	Combines spectroscopy with imaging; captures spatial-spectral data	Spatial distribution visualization, high-dimensional data, suitable for surface contamination mapping	High data volume, complex processing, expensive equipment, limited penetration depth	0.002–1 mg/kg	High	Minutes per sample
FHIS	Excitation-emission fluorescence spectra; detects photosynthetic and metabolic changes	High sensitivity to physiological stress, good for early stress detection	Requires excitation source, susceptible to ambient light, complex calibration	0.002–1 mg/kg	High	Minutes per sample
IBS	Plasma emission from laser ablation; elemental fingerprint analysis	Direct elemental detection, multi-element simultaneous analysis, minimal sample preparation	Destructive, matrix effects, requires standardization, limited reproducibility	1–10 mg/kg	Medium to High	Seconds per point
SERS	Raman scattering enhanced by nanostructures; molecular fingerprinting	Ultra-high sensitivity, molecular specificity, potential for single-molecule detection	Requires substrate preparation, signal reproducibility issues, high cost	0.001–0.1 μg/L	High	Minutes per sample
XRF	Characteristic X-ray emission from inner-shell electron transitions upon X-ray excitation	Non-destructive; portable devices available; fast; direct elemental analysis	Surface/subsurface; matrix effects; lower sensitivity light elements	1–10	Low to High	Seconds – minutes
Hyperspectral Remote Sensing	Airborne/satellite-based spectral imaging; large-area monitoring	Large-scale monitoring, non-contact, suitable for regional assessment	Low spatial resolution, atmospheric interference, indirect detection	0.1–10 mg/kg	Very High	Real-time (airborne)
ntegrated HSI & Chl-FI	Combines hyperspectral and chlorophyll fluorescence imaging	Multi-modal data, enhances early stress detection, robust modeling	Complex system integration, high cost, data fusion challenges	0.05–5 mg/kg	Very High	Minutes per sample

quantitative inversion of the content of heavy metals to be tested or the discrimination of pollution levels can be achieved.[26] Among them, Vis-NIRS, which covers the visible light region (400-700 nm), can also effectively utilize information such as pigments and colors related to electronic transitions, providing a richer spectral dimension for stress diagnosis. A complete NIRS analysis process typically includes key steps such as spectral acquisition, data preprocessing, characteristic wavelength screening, and chemometrics model establishment.[27] This indirect mechanism enables rapid and in-situ screening without damaging the sample. However, the method exhibits relatively low sensitivity for trace metals, relies heavily on robust calibration models, and is susceptible to environmental interference (*e.g.*, humidity, temperature). These characteristics position visible-near-infrared spectroscopy as more suitable for high-throughput screening purposes. The overall procedure for detecting heavy metals in crops using NIRS is illustrated in Fig. 1.

Vis-NIRS has developed relatively maturely in the field of single heavy metal pollution detection, especially performing exceptionally well in the detection of Cd pollution in grains. For instance, Zhu *et al.*[28] combined the NIRS with the siPLS algorithm to achieve rapid quantitative prediction of Cd content in brown rice, with the model prediction correlation coefficient ($R_P{}^2$) reaching 0.915. Miao *et al.*[29] successfully achieved non-destructive detection of Cd content in rice based on the biPLS algorithm. Furthermore, this technology has proven applicable to other heavy metal elements and crop types. Zhou *et al.*[31] further combined Vis-NIRS with the PLSR algorithm to construct a quantitative estimation model for Cd content in lettuce leaves, achieving high-precision assessment of Cd pollution levels.

Beyond Cd pollution detection, this technology has also achieved remarkable results in the rapid screening of other single heavy metal pollutants, and its applicable crops are no longer limited to grain crops. For example, Tang *et al.* [30] utilized the NIRS combined with the PLS-DA algorithm to achieve rapid identification of Hg contamination in Miscanthus floridulus (Labill.) Warb, with an accuracy of 100% . This fully demonstrated the broad application prospects of Vis-NIRS in the monitoring of single heavy metal pollution in crops.

At present, the application of this technology is gradually expanding from the quantitative analysis of single heavy metals towards complex pollution identification and diagnosis. In the monitoring of composite heavy metal pollution, Vis-NIRS shows significant potential by simultaneously obtaining pigment responses in the visible light region and organic matter information in the near-infrared region. Zhang *et al.*[32] achieved rapid discrimination of Cd-Pb combined stress in rice canopies using Vis-NIRS spectrum, achieving identification accuracies of 79% for Cd and 85% for Pb. Furthermore, Li *et al.*[33] introduced variational mode decomposition (VMD) and bisspectral

estimation methods, which not only enabled the identification of the elemental types of Cu-Pb contamination in corn, but also effectively monitored the degree of contamination, achieving a leap from "identifying presence or absence" to "assessing the degree" at the methodological level. The relevant progress highlights that Vis-NIRS has a promising application prospect in in-situ and non-contact field diagnosis of combined pollution stress.

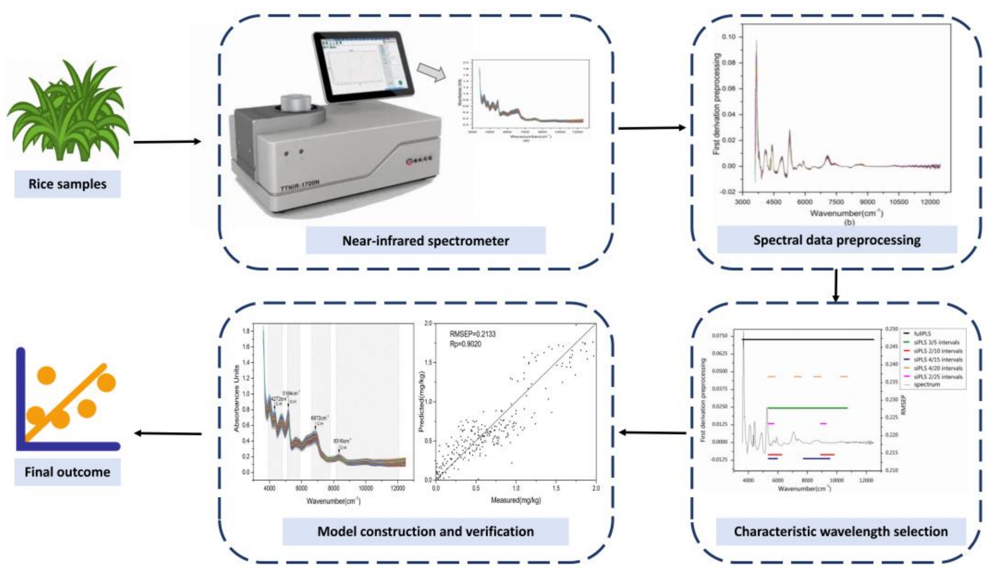


Fig. 1 The rocess of using NIRS technology to detect heavy metal in crops (redesigned from Ref. [29]).

Although Vis-NIRS can achieve efficient, non-destructive and high-precision detection of heavy metal content in crops,[34-37] this technology currently mainly relies on point source sampling to obtain spectral information of crops, ignoring the spatial distribution characteristics of samples. Because heavy metal elements in crops are often non-uniformly enriched, point source sampling is difficult to comprehensively cover the entire crop sample, which easily leads to deviations in the detection results and thus limits the promotion of this technology in practical applications.[38] Meanwhile, NIRS data itself has a high dimension and strong collinearity among variables. Especially in the analysis of trace heavy metals, the problem of spectral band overlap is prominent, which puts forward higher requirements for feature extraction and modeling algorithms.[39] The constructed models generally have the problem of insufficient universality and are easily affected by factors such as crop type, origin, and year. Usually, dedicated calibration models need to be established for specific scenarios, thus posing high requirements for users' chemometrics knowledge and model maintenance capabilities. In recent years, the portable and intelligent development of this technology has progressed rapidly. Various handheld and in-situ field detection devices have emerged, and attempts have been made to integrate them with drones and mobile terminals. This shift is driving the transition of detection modes from “point sampling” toward “area scanning,” offering new possibilities for improving spatial representativeness and detection efficiency. The application of Vis-NIRS in the detection of heavy metals in crops are shown in Table S1.[28-33]

Hyperspectral imaging spectroscopy

Principles. Hyperspectral imaging (HSI) utilizes an imaging spectrometer to capture hundreds of consecutive narrow-band images across the 400–2500 nm spectral range, simultaneously acquiring both spatial and spectral information of crop samples to form a three-dimensional data cube. This approach not only preserves the morphological and spatial distribution information of the crops but also enables the inversion of biochemical component changes induced by heavy metal stress based on the spectral characteristics of each pixel.[40]

The detection principle of HSI is based on the interaction between light and matter. When light shines on the surface of a sample, light of specific wavelengths will be absorbed or scattered, and its absorption characteristics are closely related to energy level transitions such as vibration and rotation within molecules. Heavy metal stress can can induce structural damage to chlorophyll and alter cell membrane permeability, thereby generating distinct spectral responses within specific wavelength regions.[41] To accurately obtain spectral information, whiteboard correction and dark current correction are necessary to eliminate the influence of ambient light and instrument noise and extract the true reflectance data. Further, the region of interest (ROI) is determined through image segmentation, and its average spectral curve is calculated. Subsequently, the spectral data are preprocessed and feature extracted to reduce the dimension and enhance the effective information, and ultimately a qualitative or quantitative analysis model is established.[42] The overall procedure for detecting heavy metals in crops using HSI is illustrated in Fig. 2.

Due to heavy metal stress, the internal physiological and biochemical indicators as well as the external biomass of crops will change, and their spectral reflectance and apparent morphology will also show differences.[43] HSI technology can simultaneously characterize the degree of heavy metal stress in crops from both spectral information and image features.[44] This technology has many advantages such as non-destructiveness, non-invasiveness, fast detection speed and high analysis accuracy,

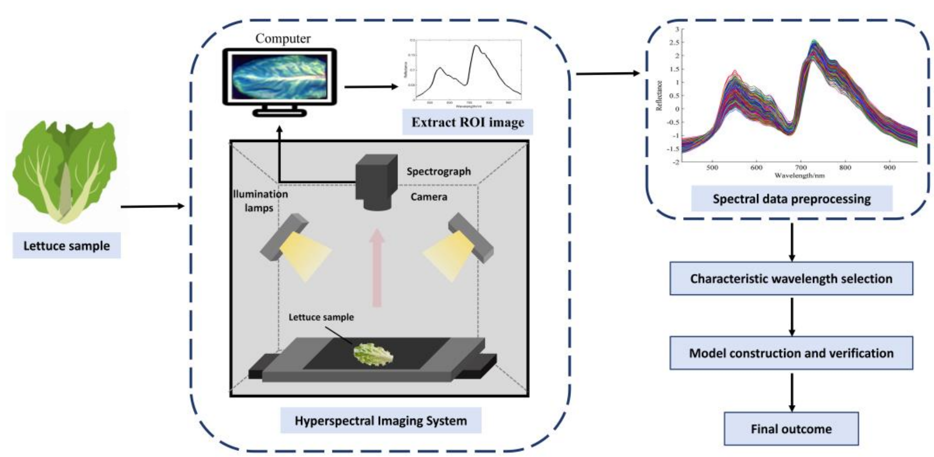


Fig. 2 The process of using HSI technology to detect heavy metal in crops (redesigned from Ref. [52]).

and has become a research hotspot at home and abroad in the identification of heavy metal stress categories in crops and the precise detection of cumulative amounts.[45]

Applications of HSI in the detection of single heavy metals. Single heavy metal pollution (such as Cd, Pb, Cu, Hg, Zn, *etc.*) frequently occurs in farmland. These heavy metals are easily absorbed and enriched by crops. By destroying cell structures and affecting physiological indicators, they form specific responses in the crop spectrum. At present, a relatively complete technical system for single heavy metal detection based on HSI has been formed, which can achieve high-precision detection of heavy metals in various crops. Some studies can also realize the visualization of pollution distribution, providing technical basis for the precise treatment of farmland contaminated by single heavy metals.

In terms of the detection of heavy metal cadmium (Cd) in crops, early research was dedicated to constructing a technical framework of "mechanism - modeling - visualization". Zhang *et al.*[46] took lettuce as the object and for the first time clarified the microscopic damage mechanism of Cd stress on leaf structure through electron microscopy observation. They also achieved high-precision prediction and spatial visualization of Cd content by combining image and spectral features, laying the foundation for the basic path of this technology.

Subsequently, the research methods began to evolve from traditional algorithms to more advanced modeling strategies. Sun *et al.*[47] innovatively combined the particle swarm optimization (PSO) algorithm with the deep belief network (DBN) to construct the PSO-DBN model, significantly improving the prediction accuracy of Cd content in lettuce and demonstrating for the first time the advantages of deep learning in this field. In the same year, Zhou *et al.*[48] focused on classification tasks and achieved high-precision discrimination of Cd stress levels in lettuce through the fusion of multiple algorithms.

The improvement of technology is further reflected in the enhancement of model performance and the diversification of the method system. Zhou *et al.*[49] optimized the weighted support vector regression (WSVR) model on the basis of the previous one, and verified the microscopic damage of Cd pollution from the mechanism level in combination with electron microscopy observations, simultaneously achieving the visual location of pollution distribution. With the expansion of the research scope, heavy metal detection models based on HSI have also made significant progress in crops such as rapeseed. Cheng *et al.*[50] innovatively introduced stacking and hybrid ensemble learning strategies, constructing a two-layer prediction framework with multiple machine learning algorithms as base learners and random forests as meta-learners. Their optimal ensemble model performed exceptionally well in the prediction of Cd content in rapeseed, with an R_P^2 as high as 0.9815, significantly enhancing the accuracy and robustness of the model.

Meanwhile, the successful application of HSI on various crops jointly proves the universality of the technique. For instance, Sun *et al.*[51] successfully achieved the quantitative determination of Cd content in tomato leaves using the wavelet transform-least squares support vector regression (WT-LSSVR) and bag of optimal sparse statistics-partial least squares regression (BOSS-PLSR) models, respectively. In 2023, Zeng *et al.*[52] proposed a novel wavelength interval selection method: the collaborative interval partial least squares method combined with the Monte Carlo method (MC-siPLS), providing a new idea for the extension of the technology to fruit and vegetable crops. In addition, Feng *et al.*[53] in Miscanthus sacchariflorus, Shen *et al.*[54] in rice, and Souza *et al.*[55] in cabbage and basil established efficient Cd content prediction models. These works collectively demonstrate that HSI combined with machine learning methods has universality and great potential in achieving rapid and non-destructive detection of heavy metals in various crops.

In terms of the detection of heavy metal lead (Pb) in crops, lettuce, as an early research object, has provided a feasible solution for the rapid detection of Pb pollution. For instance, Sun *et al.*[56] were the first to introduce the deep belief network (DBN) model into the discrimination of Pb contamination levels in lettuce, achieving an accuracy rate of 96.67%. They also realized the visualization of hyperspectral deep features through the t-distributed stochastic neighbor embedding (T-SNE) algorithm, providing an efficient solution for the rapid discrimination of Pb contamination in lettuce.

Following lettuce, research has achieved significant deepening and iteration in the crop of rapeseed. In 2021, Cao *et al.*[57] effectively optimized the parameters of the support vector regression (SVR) model by improving the random frog (MRF) algorithm in combination with the harris hawk's optimization (HHO), and initially achieved precise prediction of Pb content in rapeseed leaves. The following year, the team further upgraded the optimization algorithm to the genealy-particle swarm optimization (GA-PSO) algorithm. The performance of the MRF-GA-PSO-SVR model constructed thereby was significantly improved, marking the maturity of Pb detection technology for rapeseed. On this basis, Zhou *et al.*[58] further advanced the research method from model optimization to the innovative level of cross-domain knowledge transfer. This study introduced deep transfer learning (T-SAE) into the detection of Pb content in rapeseed leaves and roots for the first time. The model performed excellently in predicting Pb content in leaves (R_P^2=0.9215) and roots (R_P^2=0.9349), significantly enhancing the generalization ability of the model among different crop parts. However, this method is highly dependent on the migration strategy, and its universality among different crops still needs to be further verified, providing an important direction for improvement for its subsequent application. The further development of technology is reflected in the extension from detecting pollution itself to assessing the mitigation effects of pollution. Subsequently, Zhou *et al.*[59] focused on the complex physiological process of silicon (Si) -mediated alleviation of Pb stress. By proposing two improved feature wavelength extraction algorithms, repetitive interval combination optimization (RICO) and interval combination optimization (ICO) combined with stepwise regression (ICO-SR), they successfully constructed a prediction model capable of accurately quantifying the alleviating effect of Si fertilizer, providing a direct technical basis for the practical application of precision agriculture.

In addition, this technology has also been successfully extended to crops such as corn. Han *et al.*[60] applied HSI to the detection of Pb content in corn leaves, combining singular value decomposition (SVD) with adaptive fuzzy neural networks (AFNN). The established model performed excellentially, further demonstrating the universality and application potential of this technical approach in different crop types.

In terms of the detection of heavy metal copper (Cu) pollution identification and content inversion, research has presented a technical path from precise classification to quantitative prediction. Li *et al.*[61] addressed the issue of identifying Cu contamination levels in apple rootstocks by employing the competitive adaptive reweighted sampling-successive projections algorithm (CARS-SPA) for feature extraction combined with a convolutional neural network (CNN) for modeling, achieving a high classification accuracy of 99.6%. Furthermore, Zhong *et al.*[62] explored the feasibility of inverting the Cu content in the soil-wheat system using the spectra of wheat leaves. By processing the spectral data with the second derivative and screening the characteristic bands for modeling, they achieved an outstanding R_P^2 of 0.91, providing a basis for system-level Cu pollution monitoring. In addition, Lin *et al.*[63] combined continuous wavelet transform (CWT) with partial least squares (PLS) algorithm and successfully applied it to the detection of Cu content in chicory, further verifying the feasibility of implementing lightweight and rapid detection of this technology in leafy vegetable crops.

In the field of heavy metal zinc (Zn) detection in crops, Fu *et al.*[64] successfully achieved high-precision inversion of Zn content in rapeseed leaves by constructing an improved modified stacked sparse autoencoder (MSSAE) model. This study innovatively adopted the dropout mechanism and the grey wolf optimization (GWO) algorithm to collaboratively optimize the stacked sparse autoencoder (SSAE) network structure. The final model reached an R_P^2 of 0.9566, confirming the significant advantages of deep learning methods in Zn pollution detection.

In addition, this technology also shows application potential in the detection of other heavy metals. Yu *et al.*[65] applied HSI to the classification of Hg stress in tobacco. The least squares-support vector machine (LS-SVM) model constructed by extracting effective wavelengths through competitive adaptive reweighted sampling (CARS) achieved a complete distinction between non-stress and stress samples, providing a feasible solution for the early warning of lightweight Hg pollution.

Applications of HSI in the detection of compound heavy metals. With the increasingly prominent problem of complex heavy metal pollution in farmland (such as Cd-Pb, Cd-Zn, etc.), the spectral characteristics of multiple heavy metals overlap seriously. The detection task has also developed from "single content determination" to the multi-task integrated demand of "pollution identification - content prediction". HSI is gradually expanding towards complex pollution scenarios and multi-objective collaborative analysis. Relying on advanced methodologies such as deep transfer learning, multi-task neural networks, and ensemble learning, it has thus achieved breakthroughs in overcoming challenges like cross-site prediction and multi-task efficiency.

In the field of complex heavy metal detection, early research was dedicated to addressing the core issue of spectral feature overlap under combined pollution. Zhou *et al.*[66] were the first to combine wavelet transform (WT) with stacked convolutional autoencoders (SCAE). Through multi-scale spectral decomposition and automatic extraction of deep features, they successfully achieved high-precision prediction of Cd and Pb contents in lettuce leaves. Recently, Sun *et al.*[67] further proposed a hybrid feature selection based on feature clustering and symmetric uncertainty (HFCSU). The algorithm involved eliminating irrelevant features, clustering relevant features, and finally selecting representative features through differential evolution. The features most relevant to Cd and Pb pollution were precisely locked from the spectrum of rapeseed leaves. The performance of the constructed model was significantly better than that of traditional methods (Cd: R_P^2=0.9392, RPD=3.915; Pb: R_P^2=0.9442, RPD=4.702), and it had been verified by 20 independent tests to have strong robustness. Subsequently, Li *et al.*[68] further optimized on this basis and proposed the MLDF(HFCSU)-BKA-SV model, achieving better prediction results (Cd: R_P^2 = 0.9408, RMSEP = 0.1475; Pb: R_P^2 = 0.9566, RMSEP=0.1593).

In terms of multi-task detection and the improvement of model generalization ability, transfer learning and multi-task networks have become new research directions. Zhang *et al.*[69] innovatively proposed an eigenwavelength scale decomposition method for processing the spectra of corn leaves, successfully achieving the effective inversion of Cu and Pb composite pollution information. Lu *et al.*[70] proposed a combination of HSI and multi-task deep learning networks (ENet and HMNet) for the hyperenriched plant Sesteria southeast. While ENet achieved 100% accurate identification of the ecological type of heavy metal enrichment, HMNet simultaneously realized high-precision prediction of the cumulative amounts of Zn, Cd, and Pb. The RPD of the established quantitative prediction model reached 3.29, 2.57 and 2.53 respectively, opening a feasible path for the synchronous and non-destructive monitoring of different heavy metal contents in crops.

HSI has become one of the core technologies for heavy metal detection in crops. Its application has gradually expanded from the detection of single heavy metals (Cd, Pb, Cu, Hg, Zn) to the monitoring of composite pollution (Cd-Pb), and the modeling methods have been upgraded from traditional chemometrics (PLSR, SVR) to deep learning and ensemble learning. And achieve the comprehensive capability of visualizing the spatial distribution of pollution, cross-site and cross-environment prediction, and even multi-task collaborative analysis. This study reviewed key advancements over the past decade, and the results indicated that the technical system was becoming increasingly mature. The prediction accuracy of the model has been continuously improving. The coefficient of determination has generally increased from around 0.90 to above 0.98, and the performance index RPD has also been optimized from approximately 2.0 to above 7.0, demonstrating excellent predictive capabilities. Meanwhile, the application scope of the technology has been continuously expanded. The research objects have been successfully extended from early leafy vegetables such as lettuce and rape to various crops including apple rootstocks, tomatoes, miscanthus, and the enriched plant Sedum southeast, fully demonstrating the universality of the method.

However, hyperspectral imaging technology still faces several key challenges in moving toward large-scale field deployment. Firstly, the high performance of models remains heavily reliant on calibration data obtained under laboratory conditions, while the complexity of field environments—such as variations in light, temperature, humidity, and differences in crop growth stages—imposes higher demands on model robustness and adaptability. Secondly, most existing studies focus on a limited number of typical crop types and stress concentration ranges. The spectral response mechanisms under multi-variety, wide concentration spans, and combined pollution scenarios are not yet well understood, which limits the generalizability and transferability of the models. Additionally, although spatial visualization provides a powerful tool for analyzing pollution distribution, the large volume of high-resolution imaging data, complex processing requirements, and high costs restrict its application in real-time monitoring and large-scale screening. Future research should focus on model lightweighting, cross-scenario transfer learning, and the integration of low-cost imaging systems to promote the transition of this technology from laboratory research to reliable and efficient application in practical agricultural environments. In parallel, the portability and integration of HSI systems are advancing, with developments in drone-mounted and vehicle-based platforms enabling field-scale spatial monitoring. However, challenges remain in power supply, data transmission stability, and system cost, which need to be addressed to support widespread field adoption. The application of HSI in the detection of heavy metals in crops are shown in Table S2.[47-53,56-59,61,64-67,69,70]

Fluorescence hyperspectral imaging Spectroscopy

Fluorescence hyperspectral imaging (FHSI) is a non-destructive detection method based on the principle of photoluminescence. Its working mechanism involves the excitation of endogenous fluorophores in plants (*e.g.*, chlorophyll, phenolic compounds) by light of a specific wavelength, which then emit characteristic fluorescence signals.[71] Heavy metal stress alters the content and microenvironment of these fluorophores through mechanisms such as chloroplast disruption and enzyme activity interference, leading to systematic changes in the fluorescence spectral characteristics.[72,73] By simultaneously capturing the spatial distribution and spectral response of fluorescence, this technique enables early identification and visual localization of heavy metal stress in crops. The overall procedure for detecting heavy metals in crops using FHSI is illustrated in Fig. 3.

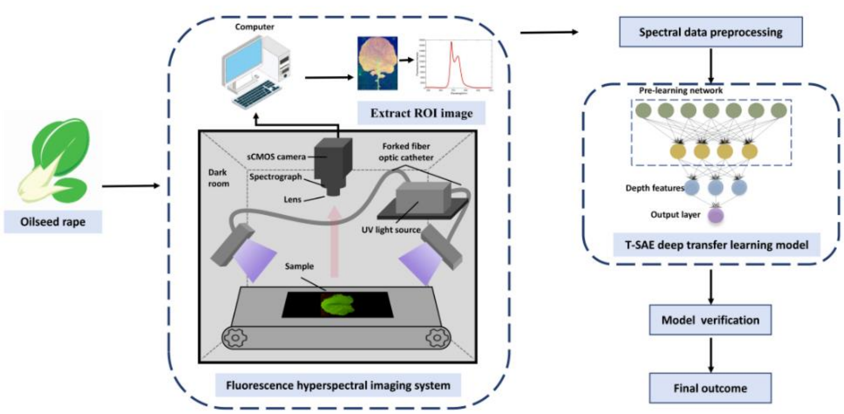


Fig. 3 The process of using FHSI technology to detect heavy metal in crops (redesigned from Ref. [78]).

FHSI retains the advantages of traditional hyperspectral technology, also possesses the high sensitivity response capability to early stress of heavy metals and the potential for visualizing spatial distribution. In recent years, with the deep integration of advanced algorithms and hardware technologies, the research focus has gradually expanded from the detection of single heavy metals to complex scenarios such as composite pollution and trace element monitoring.[74] This technology has become a cutting-edge direction in non-destructive testing of heavy metals in crops.

Single heavy metals (Cd, Pb) are common types of pollution in farmland. The application of FHSI in this field focuses on improving the efficiency of feature extraction and quantitative accuracy. Between 2021 and 2023, Zhou *et al.*[75,77] has continuously broken through the detection bottleneck through the fusion of multiple algorithms. Their research initially applied FHSI to the determination of Cd stress levels in lettuce leaves. By combining wavelet principal component analysis (WPCA) with cuckweed search optimization support vector machine (CS-SVM) model, they achieved accurate identification of different pollution levels, with an accuracy rate of 94.19%. Subsequently, they developed the wavelet transform-monte carlo optimized stacking autoencoder (WT-MC-SAE) algorithm for Pb contamination in lettuce leaves, achieving high-precision prediction of Pb content within the concentration range of 0.067-1.400 mg/kg (R_P^2=0.9467). Ultimately, they further adopted the wavelet transform-stacked denoising autoencoder (WT-SDAE) algorithm to optimize feature extraction by comparing the decomposition effects of wavelet basis functions such as sym7 and db5, achieved superior performance in the detection of Pb contamination in rapeseed leaves (R_P^2 = 0.9388, RMSEP = 0.0199 mg/kg), especially in the detection of low-concentration Pb. It is worth noting that in 2024, Zhou *et al.*[78] innovatively incorporated the environmental regulatory factor Si into the FHSI detection system, they utilized the transfer stacked convolutional autoencoder (T-SCAE) model, achieving high-precision prediction of Pb content (R_P^2= 0.9416, RMSEP = 0.01898mg/kg) and deeply revealing the inhibitory mechanism of Si on Pb absorption.

With the intensification of the complexity of farmland pollution, the cutting-edge of FHSI has extended to the fields of complex pollution and trace element detection. Zhou *et al.*[79] developed the wavelet transform-stepwise regression (WT-SR) algorithm for the spectral overlap problem caused by Cd-Pb composite contamination and constructed a multiple linear regression (MLR) model, achieving quantitative predictions of Cd (R_P^2=0.7905) and Pb (R_P^2=0.8965), respectively. At the same time, the spatial visualization characterization of heavy metal content was completed for the first time. In the field of trace element monitoring, Shi *et al.*[80] innovatively proposed the multimodal differential sensing competitive adaptive reweighted sampling (MDARS-RCNN) algorithm, which achieved high-precision detection of trace selenium (Se) in lettuce leaves under the complex environment of Cd-free and Cd environment (R_P^2=0.8975, RMSEP=0.0487 mg/kg). It has broken through the application boundaries of FHSI in heavy metal–beneficial element interaction scenarios.

FHSI enhances detection sensitivity and enables early warning by capturing chlorophyll fluorescence responses to heavy metal stress. However, this technique still has limitations in terms of signal stability and interference suppression: fluorescence signals are susceptible to environmental light, temperature, and the plant's own physiological rhythms, which may lead to fluctuations in detection results. Although the technology has evolved from traditional algorithms to intelligent models such as deep learning and transfer learning, significantly improving detection accuracy and generalization capability for both single and combined heavy metal contamination, it still faces core bottlenecks in scaling up to field applications. First, the technology itself relies on sophisticated optical equipment, and its high cost and complex operation hinder widespread adoption.[81] Second, field detection is easily disturbed by crop morphology and environmental fluctuations, imposing stringent requirements on signal stability.[82,83] Most critically, existing models lack generalizability and heavily depend on specific crop varieties and environments, leading to significant performance degradation when applied across different scenarios. There is an urgent need to develop more robust adaptive and transfer learning frameworks.[84,85] Furthermore, the development of portable FHSI devices is still in its early stages, with current systems primarily used in controlled environments. Future integration with lightweight imaging modules, real-time data processing units, and autonomous platforms could enhance its feasibility for dynamic, field-based monitoring. The application of FHSI in the detection of heavy metals in crops are shown in Table S3.[75-80]

Laser-induced breakdown spectroscopy

Laser-induced breakdown spectroscopy (LIBS) is an elemental analysis technique based on laser plasma emission. The basic principle is to generate plasma by exciting high-energy pulsed laser on the sample surface. By analyzing the characteristic spectral intensity and wavelength of specific wavelengths during the cooling process of the plasma, qualitative and quantitative analysis of heavy metal elements can be achieved.[86,88] LIBS technology has rapidly developed in the field of heavy metal detection in crops due to its unique advantages such as rapid response, micro-destructiveness, minimal or no sample preparation required, and especially the simultaneous detection of multiple elements.[89,90] Its research has gradually evolved from the analysis of single pollution targeting specific elements to the simultaneous screening and assessment of complex pollution caused by the interaction of multiple elements. The overall procedure for detecting heavy metals in crops using LIBS is illustrated in Fig. 4.

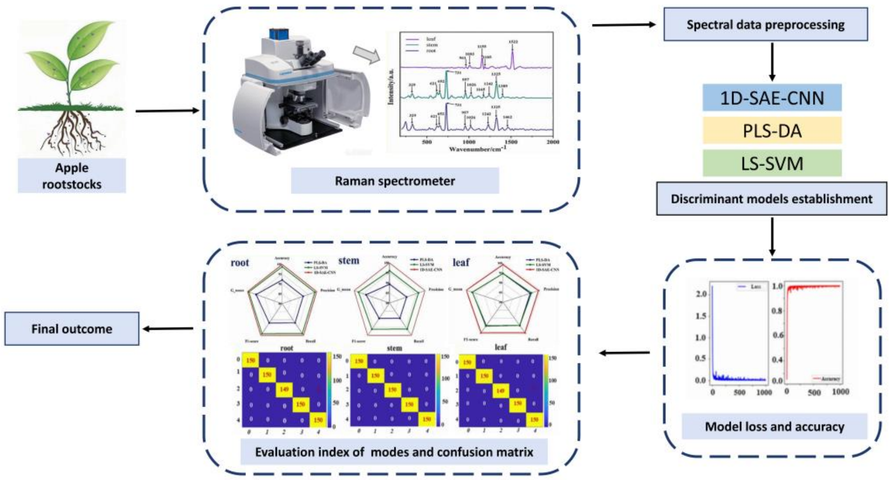


Fig. 4 The process of using LIBS technology to detect heavy metal in crops (redesigned from Ref. [102]).

Applications of LIBS in the detection of single heavy metals. The development of LIBS technology in the field of single heavy metal detection clearly demonstrates a systematic research path from qualitative screening, precise quantification to mechanism exploration. Early research mainly verified its qualitative identification ability. It successfully detected elements such as copper (Cu), silver (Ag), and lead (Pb) in various crop systems including spruce, sunflower, and pepper,[91-95] initially demonstrating the potential of LIBS for qualitative identification and semi-quantitative analysis of heavy metals in crops.

To achieve precise quantification, the research focus has shifted to chemometrics modeling and variable selection. In the field of Cd pollution detection, Shen *et al.*[96] combined genetic algorithm (GA) with partial least squares regression (PLS) to achieve high-precision prediction of Cd content in lettuce (R_P^2=0.9716), and utilized the random forest (RF) algorithm to achieve 100% accurate classification of pollution levels. Wang *et al.*[97] constructed a quantitative model for rice stems using wavelet transform (WT) and extreme learning machine (ELM), and increased the prediction correlation coefficient to 0.995. In the detection of other single elements, Liu *et al.*[98] accurately evaluated Cu contamination in rice using support vector machine regression (SVM), achieving an R_P^2 of 0.9879. Peng *et al.*[99] enhanced the signal through dual-pulse LIBS, achieving an RPD of 9.70 for the rice Cd content prediction model and significantly improving the detection sensitivity.

It is worth noting that the application of LIBS has extended from simple content detection to the level of mechanism research. For instance, Tripathi *et al.*[100] monitored changes in Pb content in wheat seedlings before and after Si treatment, revealing the mitigating effect of Si on Pb toxicity, providing another approach for exploring how Si alleviates heavy metal toxicity.

Applications of LIBS in the detection of complex heavy metals. The core advantage of LIBS lies in its ability to conduct multi-element synchronous analysis, which makes it demonstrate unique value in the assessment and source tracing of complex pollution. Multivariate statistics and machine learning methods are widely applied to extract effective information from complex spectral data.[101]

In terms of algorithmic strategies, to break through the dual limitations of high dimensionality and small sample size of LIBS data, the research methods show an evolutionary trend from feature selection to data reconstruction and feature collaborative optimization. Heiner *et al.*[102] enhanced the data through normal distribution sampling and combined random forest (RF) feature selection to achieve dual dimensionality reduction, significantly improving the detection accuracy of Cu and Cr in mulberry leaves. Subsequently, Yang *et al.*[103] constructed a novel analysis framework consisting of a Kohonen self-organizing map (SOM) with variable selection and consensus modeling for LIBS data, achieving high-precision determination of Cu and Cr content ((Cu: RPD = 10.0494, RMSEP = 110.4550; Cr: RPD = 8.3874, RMSEP = 41.4561). Huang *et al.*[104] proposed a new method based on cross-calculation of total variables and characteristic variables (CCFCV), which achieved excellent results in the prediction of Cr and Cu content in mulberries, with RPD values of 3.900 and 4.771, respectively. This approach provided an innovative solution for the extraction of multi-element spectral information.

In terms of multi-element synchronous quantification, Salloom *et al.*[105] conducted synchronous detection of Cr, Pb, Cu, and Cd in 12 commercially available rice varieties, and combined principal component analysis (PCA) with radar charts to achieve the differentiation and traceability of pollution characteristics. Zhao *et al.*[106] adopted an intermediate data fusion strategy to establish a high-precision prediction model for Zn, Cu, and Pb in lily bulbs (R_P^2: 0.9858, 0.9811, 0.9460), and showcasing enhanced multi-element detection through integrated multi-dimensional information. Fayek *et al.*[107] simultaneously determined multiple elements such as Fe, Zn, Mn, Ni, Pb, and Cr in the roots and buds of clover using calibration-free picosecond LIBS technology (CF-PS-LIBS), and analyzed the relationship between plasma parameters and heavy metal concentrations. It provided a new quantitative basis for multi-element detection.

The current research frontier is further integrating artificial intelligence technology. Peng *et al.*[99] applied wasserstein generative adversarial networks (WGAN) to LIBS data augmentation, achieving high-precision visualization of heavy metal distribution in rice leaves under Cr stress, providing a new method for studying the migration patterns of heavy metals in plants.

Based on the above progress, LIBS technology has demonstrated significant value in laboratory-based quantitative analysis of heavy metals in crops, owing to its advantages such as simultaneous multi-element detection, minimal sample preparation, and rapid analysis. Through the integration of advanced algorithms and hardware design, this technology has successfully evolved from single-element quantification to multi-element joint detection and multi-task analysis.[108] However, it still faces notable challenges in practical agricultural applications. Firstly, LIBS detection results are susceptible to matrix effects and sample surface morphology, leading to insufficient reproducibility of quantitative models across different crop tissues, moisture contents, and textures. Secondly, most current studies remain limited to laboratory-prepared samples or excised tissues, and its adaptability for in-situ live detection in field conditions requires further validation. Furthermore, issues such as high instrument costs, strong requirements for operational expertise, and interference of spectral signals by environmental factors also hinder its widespread adoption in large-scale field screening. Notably, while several commercial handheld LIBS devices are available, their performance in complex agricultural settings is often constrained by limited spectral stability and the need for frequent recalibration. Future system integration should emphasize robustness against environmental variables, automated sampling interfaces, and cloud-based model updating to enhance field reliability. Therefore, future research should focus on developing matrix effect correction models, creating miniaturized and portable systems suitable for complex field environments, and exploring real-time analysis strategies deeply integrated with machine learning, thereby promoting the transition of this technology from the laboratory to stable and reliable on-site agricultural applications.[109] The application of LIBS in the detection of heavy metals in crops are shown in Table S4.[96-99,102,103,105,106]

Surface-Enhanced Raman Spectroscopy

Surface-Enhanced Raman Spectroscopy (SERS) enables highly sensitive detection of molecular vibrational fingerprints by significantly enhancing Raman scattering signals through localized electromagnetic field enhancement and chemical enhancement effects on nanostructured surfaces. In the detection of heavy metals in crops, heavy metal stress induces molecular-structural changes in biochemical components (*e.g.*, proteins, polysaccharides, pigments) within plant tissues, which subsequently alter their characteristic Raman spectra.[110-115] By capturing these differences in molecular fingerprints, SERS can indirectly reflect the degree of heavy metal contamination. Current research primarily focuses on the stress response to single heavy metals and qualitative-to-semiquantitative discrimination. The overall procedure for detecting heavy metals in crops using SERS is illustrated in Fig. 5.

In terms of Cu pollution detection, Li *et al.*[116,117] were the first to combine SERS with a stacked auto-encoder convolutional neural network (SAE-CNN) model. By analyzing the root system, stems and leaves of apple rootstocks under Cu stress, they achieved

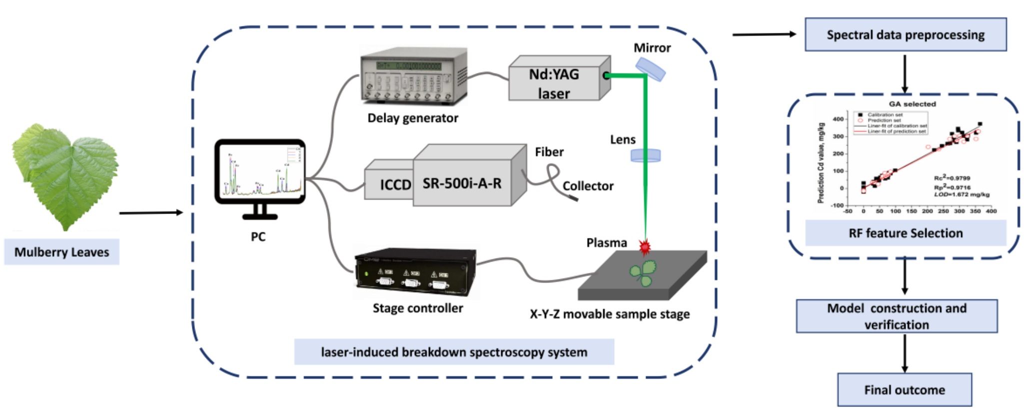


Fig. 5 The process of using SERS technology to detect heavy metal in crops (redesigned from Ref. [117]).

rapid discrimination of the Cu stress level of heavy metals, with a model accuracy rate exceeding 99%. The following year, they further optimized the SAE-CNN model, combining scanning electron microscopy - energy dispersive spectroscopy analysis and micro-area Raman imaging technology. This approach not only visualized the migration and distribution characteristics of Cu ions in apple rootstock tissues but also revealed the low-concentration promotion and high-concentration inhibition effect of Cu stress on plant growth, with all model evaluation indicators exceeding 0.9.

In terms of arsenic (As) pollution detection, research focuses on developing highly sensitive quantitative methods. Barimah *et al.*[118] achieved precise quantification of total As in tea by using unlabeled Cu_2O/Ag SERS nanoprobes and combining the competitive adaptive reweighted sampling partial least squares (CARS-PLS) algorithm. The R_P^2 was as high as 0.9935, and the RMSEP was as low as 0.00561 μg−1.The study compared the SERS results with those obtained by inductively coupled plasma mass spectrometry (ICP-MS) on the same batch of tea samples, and statistical analysis showed no significant difference ($P > 0.05$), indicating that under this specific experimental setup, the SERS method exhibited quantitative capability comparable to that of ICP-MS. Nevertheless, SERS technology still lags far behind ICP-MS in terms of universality across complex real-world matrices, quantitative stability, and degree of standardization; its performance remains highly dependent on probe design, sample pretreatment procedures, and modeling algorithms. Juarez *et al.*[119] successfully identified As stress in four rice varieties under hydroponic conditions by using RS combined with partial least squares discriminant analysis (PLS-DA) model, with a model accuracy rate of 89%.

In the field of Pb pollution detection, Wang *et al.*[120] took vetivegrass, a plant rich in heavy metal Pb, as the object and innovatively combined D401 resin adsorption technology with RS. After savitzky-golay smoothing combined with first derivative (SG-FD) preprocessing, a partial least squares quantitative (PLS) model was established, and the Rp^2 reached 0.854. The feasibility of this method for detectingPb content in plant roots has been confirmed.

In the field of Cd pollution detection, Chen *et al.*[121] achieved rapid and high-precision detection of trace Cd in tea by combining surface-enhanced Raman technology with first-order derivative (FD) and competitive adaptive reweighted sampling (CARS) algorithms.

However, relying solely on single molecular fingerprint information still struggles to fully overcome matrix interference and achieve accurate quantification when dealing with complex agricultural samples. Future developments in this field should focus more on multi-technology integration and intelligent algorithm co-innovation. For instance, in a study evaluating lead (Pb) stress on wheat seedlings, Yang *et al.*[122] systematically compared various discrimination models constructed based on single SERS, double-pulse LIBS (DP-LIBS), and their fused spectra (LIBS–Raman). The results demonstrated that the model built on LIBS–Raman fused data significantly outperformed models based on any single-technology data in terms of classification accuracy and stability. This suggests that promoting the combined use of SERS with atomic spectroscopy techniques such as LIBS and XRF, along with integrating advanced algorithms like deep learning for feature fusion and collaborative modeling,[123-125] can effectively compensate for the limitations of single-technology approaches, which are often characterized by incomplete information and weak anti-interference capabilities. This integrated strategy represents an effective pathway to overcome the bottlenecks of single-technology detection, enabling higher accuracy and stronger anti-interference performance. It also opens new directions for highly reliable quantitative detection of heavy metals in crops with complex matrices. The application of SERS in the detection of heavy metals in crops are shown in Table S5.[116-119,121]

Advanced detection techniques and fusion strategies

The aforementioned chapter systematically discusses the application of mainstream spectral techniques such as Vis-NIRS, HSI, FHSI, LIBS, and SERS in the detection of heavy metals in crops. This chapter will focus on two cutting-edge directions in this field: the first is to introduce emerging spectral technologies that go beyond the traditional optical spectrum; The second is to elaborate on the innovative strategy of breaking through the detection bottleneck of a single technology through the integration of multi-spectral technologies.

Emerging non-destructive testing technology. Beyond traditional optical spectroscopy, technologies such as terahertz (THz) and microwave (MW), with their unique physical mechanisms, have opened new paths for heavy metal detection in crops. The detection band of terahertz spectroscopy (0.1-10 THz) can excite the lattice vibration of heavy metal compounds and sense the collective mode of biological macromolecules, thereby simultaneously obtaining information on the morphology of heavy metals and the biochemical stress they trigger. Moreover, its low photon energy characteristic ensures the non-destructive nature of the detection process to biological samples.[126,127] Microwave detection technology is based on the principle that heavy metal ions disturb the electromagnetic properties of the medium. It achieves detection by analyzing the changes in microwave propagation parameters (such as amplitude and phase), and is sensitive to conductive substances. It also has the advantages of simple equipment that can be integrated and is suitable for rapid online analysis.[128]

Zhu *et al.*[129,130] applied MW to screen trace Cd in peanut oil.

Through analyzing the MW transmission index and constructing an optimized metrological model, they achieved high-precision quantification with R_P^2 of 0.9944 and accurate pollution level discrimination with 100% accuracy. Lu *et al.*[131] utilized THz to achieve simultaneous detection of multiple elements such as Hg, Cd, Cu. The machine learning-integrated model they developed demonstrated excellent predictive performance, with optimal R_P^2 values surpassing 0.95, thereby validating the potential of THz for rapid, non-destructive qualitative and quantitative analysis of heavy metals in complex media.

At the remote sensing scale, hyperspectral remote sensing technology also demonstrates its ability to detect heavy metal pollution in crops. For instance, Zhou *et al.*[132] utilized hyperspectral remote sensing data to detect the Cd content in brown rice through a partial least squares regression (PLSR) model, with R_P^2 reaching 0.873. Zhong *et al.* [133] focused on wheat leaves and simultaneously achieved the detection of Cd and As content by combining a optimized GA-PLSR model. Among them, the R_P^2 of Cd is 0.87 and the RPD is 2.72. The predictive performance of As is better, with R_P^2 reaching 0.91 and RPD reaching 3.25. These studies have confirmed the feasibility of hyperspectral remote sensing technology for synchronous monitoring of multiple heavy metal pollution at the field scale.

In addition, the successful application of techniques such as laser-induced fluorescence (LIF)[134] and attenuated total reflection-Fourier Transform infrared spectroscopy (ATR-FTIR)[135] in the detection of Cu stress in corn seedlings has further expanded the spectral technology system for non-destructive detection of heavy metals in crops.

Multispectral technology fusion strategy. While exploring emerging spectral detection technologies, systematically integrating spectral techniques of different principles and spectral bands, and constructing a more comprehensive heavy metal stress diagnosis map through information complementarity, has become an inevitable trend to break through the bottleneck of single technology detection.

At the level of optical internal fusion, Zhang *et al.*[136] innovatively combined HSI with chlorophyll fluorescence imaging (Chl-FI), thereby simultaneously obtaining biochemical component information and photosynthetic physiological function information of crops. By constructing an end-to-end deep learning fusion model, its recognition accuracy rate for Cd and Cu stress in rice is as high as 97.7%. Fu *et al.*[137] innovatively started from the frequency domain perspective and combined empirical mode decomposition (EMD) with power spectral density (PSD) to construct the EMD-PSD method, achieving an effective distinction of Cu and Pb stress types in corn leaves.

At the level of cross-spectral band and cross-sensor coupling, research has demonstrated broader compatibility. Li *et al.*[138] successfully fused X-ray fluorescence (XRF) with mid-infrared (MIR) spectroscopy at the data layer. This strategy fully exploits the advantages of direct elemental analysis by XRF and the rich molecular structure information of MIR. With a maximum R_P^2 of 0.98 for As and Cr, the prediction accuracy significantly surpasses that of a single sensor. Similarly, Yang *et al.*[103] combined SERS with LIBS, and the performance of their model was also comprehensively superior to that of a single technology. Li *et al.*[139] utilized the latest grating array full-spectrum detection technology (GAFSDT) to detect the Cu and Pb contents in corn leaves. Combined with the VMD-PCA-SVM model, they achieved a prediction accuracy rate of approximately 0.8, demonstrating the potential of full-spectrum information mining in complex substrate detection.

The emerging spectral technology and the multi-technology integration strategy jointly constitute the future picture of the development of heavy metal detection technology for crops. However, to transform it into a universal tool, core challenges still need to be overcome: the primary task is to establish a standardized process for multi-source data fusion and develop an adaptive general algorithm architecture; Meanwhile, there is an urgent need to promote the evolution of detection equipment towards portability, low cost and high environmental robustness, so as to truly meet the application requirements of complex field scenarios.[140-142] The application of other detection technologies in the detection of heavy metals in crops are shown in Table S6.[132,133,136,139]

CONCLUSIONS AND PROSPECT

The application status and comparative performance of the mainstream spectroscopic and imaging techniques reviewed in this article are systematically summarized in Table 1. This comparative overview synthesizes the fundamental detection principles, core advantages, inherent limitations, typical limits of detection (LOD), relative cost levels, and approximate analysis speeds for each technology, including Vis-NIRS, HSI, FHSI, LIBS, SERS, XRF, Hyperspectral Remote Sensing, Integrated HSI & Chl-FI, and XRF. The table provides a consolidated framework that clearly delineates the complementary roles and practical trade-offs among these methods in addressing the challenge of heavy metal detection in crops.

This review systematically summarizes the research progress and application status of spectroscopic and imaging technologies in the non-destructive detection of heavy metals in crops over the past two decades. Crop heavy metal detection technologies based on spectroscopy can be classified into two categories based on their principles: atomic spectroscopy for direct elemental content determination and molecular spectroscopy/imaging for indirect assessment of stress effects. Molecular spectroscopic techniques detect heavy metal stress indirectly by capturing the resulting physiological and biochemical changes in crops. For instance, Vis-NIRS based on overtone and combination vibrations of hydrogen-containing functional groups, rapidly reflects the physiological response under heavy metal stress. HSI and FHSI integrate spatial dimensions with molecular spectral information, enabling the visualization of pollution distribution and early diagnosis. SERS relies on the nano-enhancement effect to capture the fingerprint signals of interactions between heavy metal ions and biomolecules, demonstrating great potential for trace-level detection. Atomic spectroscopic techniques, on the other hand, enable direct qualitative and quantitative analysis of heavy metal elements. For example, LIBS achieves simultaneous multi-element determination through the atomic/ionic emission lines from laser-induced plasma. Similarly, XRF also based on atomic energy level transitions, provides direct elemental content information suitable for rapid screening and quantitative analysis.[143-148] By capturing changes in crop physiological and biochemical parameters (e.g., chlorophyll content, cell structure, water metabolism) and phenotypic characteristics under heavy metal stress, these technologies have successfully achieved qualitative identification, quantitative inversion, and spatial visualization of pollution for various heavy metals such as Cd, Pb, Cu, Hg, Cr and As. The deep integration of chemometrics with machine learning and deep learning algorithms has significantly enhanced the prediction accuracy, robustness, and interpretability of models, positioning non-destructive detection as a vital supplement and even an alternative to traditional chemical analysis methods.[149]

Currently, the performance characteristics and application scopes of these technologies have become distinctly differentiated. Vis-NIRS, with its advantages of speed, low cost, and portability, has become an effective tool for preliminary field screening and crop health monitoring, particularly suitable for indirect assessment of pollution like Cd and Pb. However, its detection limit is typically high (> 0.1 mg/kg), and model performance heavily relies on robust calibration datasets.[150] HSI and FHSI, by incorporating spatial information, enable the visualization and early diagnosis of physiological responses to heavy metal stress, showing unique value in mapping the spatial distribution of pollutants like Cd, Pb, and Cu at the leaf scale. Nevertheless, their high system cost, large data volume, and complex processing confine their primary use to laboratory and controlled-environment research. As a typical atomic spectroscopy technique, LIBS offers simultaneous multi-element detection and accurate quantification with detection limits reaching the ppm level, playing a crucial role in laboratory precision analysis. However, its micro-destructive nature, significant matrix effects, and requirement for sample homogeneity limit its application in continuous in vivo and in situ monitoring. SERS technology, with its extremely high sensitivity (reaching ppb levels), shows immense potential for detecting trace heavy metals like As and Hg.[151-154] Yet, challenges remain regarding signal reproducibility, substrate uniformity, and standardized fabrication processes.

It is noteworthy that a gap persists between the detection performance of existing technologies and the requirements of agricultural product safety standards. Although numerous studies report good predictive accuracy, the practical detection limit (LOD) of most methods remain substantially higher than the most stringent current safety standards for agricultural products (Pb: GB 2762-2022, Zn: GB 5009.14-2017, Cd: GB 5009.15-2023, As: GB 5009.11-2014, Hg: GB 5009.17-2014, Cr: GB 5009.123-2014, Multi-element: GB 5009.268-2025).[155] Except for SERS and some extensively optimized LIBS methods, the LOD of most spectroscopic technologies exceed these standard limit values by an order of magnitude or more. This indicates that the current sensitivity of these technologies is still insufficient to meet the detection requirements for trace-level pollution in practical regulatory scenarios.

Despite this, the application of this technological system offers multi-dimensional value for agricultural product quality and safety control: (1) It enables early and rapid pollution screening and severity assessment, providing key technical support for preventing contaminated products from entering the market at the production source; (2) Its non-destructive and repeatable monitoring characteristics facilitate tracking pollution dynamics and remediation effects, serving precision agriculture; (3) The multi-element simultaneous analysis capability of technologies like HSI and LIBS opens new avenues for identifying and tracing compound pollution; (4) With the development of portable and low-cost devices, this technology holds promise for integration into the entire agricultural product quality and safety supervision chain, enhancing industry transparency and consumer trust.

Current major challenges. Despite significant advancements, spectroscopic and imaging technologies face a series of core challenges in their transition to large-scale practical application. First, each technology has inherent limitations. Vis-NIRS and HSI are susceptible to interference from ambient light, crop phenotypic structure, and background noise. LIBS is significantly affected by matrix effects, and its plasma signal stability needs improvement. While SERS offers high sensitivity, its quantitative accuracy is easily compromised by complex sample matrices. Second, model performance is severely constrained by transferability and generalizability.[156-159] Most existing detection models are built on data from specific crop varieties, growth environments, and years. Their weak adaptability to the complex matrix effects introduced in real-field applications, including variations in crop growth stages, soil background, environmental fluctuations, and sample surface contamination, severely limits the widespread applicability of this technology. Furthermore, the practical detection limits of most technologies cannot fully meet the increasingly stringent regulatory demands for trace pollutants set by agricultural product safety standards. In addition, high cost and limited accessibility are significant constraints. Systems like HSI and LIBS are expensive, require specialized operation, and involve high technical thresholds for data processing, making them difficult to popularize among grassroots field technicians and small-to-medium scale producers.[160-162] Finally, a unified technical standard system is yet to be established in this field. The absence of a standardized framework encompassing data collection protocols, model validation methods, and pollution discrimination thresholds hinders the standardized development and industrial application of these technologies.

Future Development Directions. To advance the deep application of spectroscopic and imaging technologies in crop heavy metal detection from the laboratory to the field, future research should focus on the following directions:

Addressing matrix effects and model transferability to build robust analytical models. The core lies in constructing large-scale, diverse, and cross-growth-cycle public standard databases pairing spectra with concentration data. Research should explore calibration models based on advanced algorithms like deep transfer learning, domain adaptation, meta-learning, and physics-informed embedding.[163] The goal is to develop models adaptable to different varieties, environments, and growth stages, reducing dependence on massive locally labeled datasets.

Promoting multi-modal sensing and cross-scale technology fusion for collaborative detection pathways. Breaking the limitations of single technologies requires building a hierarchical detection system based on "multi-scale collaboration." For instance, drone-borne HSI can be used for rapid localization of contaminated areas at the field scale, combined with portable LIBS or micro-XRF for in-situ, minimally-destructive quantitative verification and elemental distribution imaging of key samples. This fusion enables correlative analysis between the physiological response to heavy metal stress and the spatial distribution of elements, enhancing detection efficiency and reliability.

Advancing equipment engineering, intelligence, and networking for field deployment. Hardware development must focus on environmental light shielding, built-in real-time self-calibration modules, temperature and humidity compensation, and rugged packaging design. On the data processing front, robust feature extraction methods insensitive to non-target variations need to be developed. The core objective is to achieve deep adaptation and system integration of multi-spectral sensing modules with heterogeneous mobile platforms like smartphones and drones.

Establishing a full-chain technical standard system and expanding application scenarios. It is crucial to systematically formulate comprehensive standards covering spectral data collection, model validation, performance evaluation, and pollution discrimination. Standardized detection technology should be integrated into the entire supervision network.[164-166] This includes all stages from origin screening and purchase inspection to processing monitoring. Such integration would enable real-time risk assessment and traceability through cloud-based platforms. Furthermore, future research needs to expand the capability for simultaneous detection and identification of combined pollution involving multiple heavy metals and their combined stress with organic pollutants such as pesticides.

Summary. Spectroscopic and imaging technologies provide powerful tools for the non-destructive and rapid detection of heavy metal pollution in crops, having achieved significant progress in mechanistic understanding, methodological development, and application validation. A complementary technical framework comprising indirect assessment via molecular spectroscopy and direct quantification via atomic spectroscopy has been established. Currently, the field is at a critical transitional phase from "laboratory validation" to "field practicality." Future sustained efforts focusing on key areas such as model robustness, multi-technology fusion, equipment engineering, standard system construction, and composite pollution detection capabilities are expected to overcome current bottlenecks. This will facilitate the leap from laboratory research to field application in agricultural product quality and safety, contributing substantially to ensuring global food security and human health.

ASSOCIATED CONTENT

The supporting information (Tables S1-S6) is available at https://www.at-spectrosc.com.

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Notes

The authors declare no competing financial interest.

ACKNOWLEDGMENTS

This work is partially supported by the Project funded by the National Natural Science Funds Projects (32201653), the China Postdoctoral Science Foundation (2021M701479), the Project of Faculty of Agricultural Engineering of Jiangsu University (NGXB20240202), the Priority Academic Program Development of Jiangsu Higher Education Institutions (PAPD), and the Scientific research funding projects for students of Jiangsu University (24A174).

REFERENCES

1. M. El-Sharkawy, J. Li, N. Kamal, E. Mahmoud, A. E. D. Omara, and D. Du, *J. Soil Sci. Plant Nutr.*, 2023, **23**, 6510-6526. https://doi.org/10.1007/s42729-023-01507-w
2. R. Kama, Y. Liu, M. Aidara, D. F. Kpalari, J. Song, S. Diatta, and Z. Li, *J. Soil Sci. Plant Nutr.*, 2024, **24**, 7090-7104. https://doi.org/10.1007/s42729-024-02026-y
3. A. R. Khan, A. Salam, G. Li, B. Iqbal, Z. Ulhassan, Q. Liu, and D. Du, *Crop J.*, 2024, **12**, 1280-1298. https://doi.org/10.1016/j.cj.2024.09.010
4. A. Jalal, Y. Wang, C. Cai, A. Ayaz, K. F. Alabbosh, K. A. Khan, and D. Zhu, *J. Agron. Crop Sci.*, 2025, **211**, e70012. https://doi.org/10.1111/jac.70012
5. J. Wang, Q. Chen, T. Belwal, X. Lin, and Z. Luo, *Compr. Rev. Food Sci. Food Saf.*, 2021, **20**, 2476-2507. https://doi.org/10.1111/1541-4337.12741
6. G. Cen, T. Sun, Y. Chen, W. Wang, A. Feng, A. Liu, and C. You, *Gene*, 2022, **822**, 146331. https://doi.org/10.1016/j.gene.2022.146331
7. M. A. Farooq, S. Ali, A. Hameed, W. Ishaque, K. Mahmood, and Z. Iqbal, *Ecotoxicol. Environ. Saf.*, 2013, **96**, 242-249. https://doi.org/10.1016/j.ecoenv.2013.07.006
8. Y. H. Kim, A. L. Khan, M. Waqas, and I. J. Lee, *Front. Plant Sci.*, 2017, **8**, 510. https://doi.org/10.3389/fpls.2017.00510
9. P. Peiró-Vila, C. Pérez-Gracia, J. J. Baeza-Baeza, M. C. García-Alvarez-Coque, and J. R. Torres-Lapasió, *J. Chromatogr. A*, 2024, 1730, 465128. https://doi.org/10.1016/j.chroma.2024.465128
10. H. R. Tan, L. Y. Chan, A. Ong, Y. Q. Xu, X. B. Zhang, and W. Zhou, *Food Chem.*, 2023, **408**, 135135. https://doi.org/10.1016/j.foodchem.2022.135135
11. N. Altunay, A. Elik, and R. Gürkan, *Food Chem.*, 2019, **293**, 378-386. https://doi.org/10.1016/j.foodchem.2019.05.019
12. Y. Z. Lu, Y. P. Chen, H. F. Xie, B. Cao, Q. Li, Y. Sun, and Q. L. Yuan, *Environ. Sci.*, 2025, **46**, 1783-1794. https://doi.org/10.13227/j.hjkx.202401260
13. M. Adrees, S. Ali, M. Rizwan, M. Zia-ur-Rehman, M. Ibrahim, F. Abbas, and M. K. Irshad, *Ecotoxicol. Environ. Saf.*, 2015, **119**, 186-197. https://doi.org/10.1016/j.ecoenv.2015.05.011
14. V. Shah, and A. Daverey, *J. Clean. Prod.*, 2021, **280**, 124406. https://doi.org/10.1016/j.jclepro.2020.124406
15. I. Khan, S. A. Awan, M. Rizwan, S. Ali, M. J. Hassan, M. Brestic, and L. Huang, *Ecotoxicol. Environ. Saf.*, 2021, **222**, 112510. https://doi.org/10.1016/j.ecoenv.2021.112510
16. H. Ahmad, J. Sun, A. Nirere, N. Shaheen, X. Zhou, and K. Yao, *J. Food Process. Preserv.*, 2021, **45**, e15241. https://doi.org/10.1111/jfpp.15241
17. Z. Zhang, and L. Deng, *J. Food Process. Preserv.*, 2024, **2024**, 5876051. https://doi.org/10.1155/2024/5876051
18. J. Molina M, R. Pincay, V. Santos, J. L. González, M. F. Trujillo Guerrero, D. Díaz Pace, and C. Costa-Vera, *Sensors*, 2025, **25**, 2434. https://doi.org/10.3390/s25082434
19. Z. Guo, P. Chen, L. Yin, M. Zuo, Q. Chen, H. R. El-Seedi, and X. Zou, *Food Control*, 2022, **132**, 108498. https://doi.org/10.1016/j.foodcont.2021.108498
20. J. Zhang, X. Wu, C. He, B. Wu, S. Zhang, and J. Sun, *Foods*, 2024, **13**, 1439. https://doi.org/10.3390/foods13101439
21. D. Zhang, H. Ma, J. Nie, Y. Liu, and L. Guo, *Talanta*, 2025, **281**, 126872. https://doi.org/10.1016/j.talanta.2024.126872
22. Y. X. Zhao, and H. Y. Wang, Feed Ind., 2005, **26**, 37-41.
23. S. Park, S. Jeon, N. H. Kwon, M. Kwon, J. H. Shin, W. C. Kim, and J. G. Lee, *Eur. J. Agron.*, 2024, **159**, 127228. https://doi.org/10.1016/j.eja.2024.127228
24. M. E. Hossain, M. A. Kabir, L. Zheng, D. L. Swain, S. Mcgrath, and J. Medway, *Heliyon*, 2024, **10**, e40016. https://doi.org/10.1016/j.heliyon.2024.e40016
25. P. Suran, *Hortic. Sci.*, 2024, **51**, 169-188. https://doi.org/10.17221/85/2023-hortsci
26. J. Zeng, Y. Guo, Y. Q. Han, Z. M. Li, Z. X. Yang, Q. Q. Chai, W. Wang, Y. Zhang, and C. L. Fu, *Molecules*, 2021, **26**, 749. https://doi.org/10.3390/molecules26030749
27. W. Luo, D. Wang, Z. Xu, G. Liao, D. Chen, X. Huang, Y. Wang, S. Yang, L. Zhao, H. Huang, Y. Li, W. Wei, Y. Long, and Z. Du, *Environ. Int.*, 2020, **143**, 105898. https://doi.org/10.1016/j.envint.2020.105898
28. X. Zhu, G. Li, and Y. Shan, *Int. J. Food Sci. Technol.*, 2015, **50**, 1123-1129. https://doi.org/10.1111/ijfs.12756
29. X. Miao, Y. Miao, H. Gong, S. Tao, Z. Chen, J. Wang, Y. Chen, and Y. Chen, *Spectrochim. Acta A*, 2021, **257**, 119700. https://doi.org/10.1016/j.saa.2021.119700
30. B. C. Tang, H. Y. Fu, Q. B. Yin, Z. Y. Zhou, W. Shi, L. Xu, and Y. B. She, *J. Spectrosc.*, 2016, **2016**, 3597451. https://doi.org/10.1155/2016/3597451
31. L. Zhou, L. Zhou, H. Wu, T. Jing, T. Li, J. Li, and L. Chen, *Agronomy*, 2024, **14**, 644. https://doi.org/10.3390/agronomy14040644
32. S. Zhang, J. Li, S. Wang, Y. Huang, Y. Li, Y. Chen, and T. Fei, *Remote Sens.*, 2020, **12**, 469. https://doi.org/10.3390/rs12030469
33. Y. Li, K. Yang, B. Wu, J. Zhang, Q. Han, and W. Gao, *Environ. Sci. Pollut. Res.*, 2023, **30**, 14155-14164. https://doi.org/10.1007/s11356-022-23206-2
34. J. Wieme, K. Mollazade, I. Malounas, M. Zude-Sasse, M. Zhao, A. Gowen, D. Argyropoulos, S. Fountas, and J. Van Beek, *Biosyst. Eng.*, 2022, **222**, 156-176. https://doi.org/10.1016/j.biosystemseng.2022.07.013
35. A. Bhargava, A. Sachdeva, K. Sharma, M. H. Alsharif, P. Uthansakul, and M. Uthansakul, *Heliyon*, 2024, **10**, e33208. https://doi.org/10.1016/j.heliyon.2024.e33208
36. A. Gowen, C. Odonnell, P. Cullen, G. Downey, and J. Frias, *Trends Food Sci. Technol.*, 2007, **18**, 590-598. https://doi.org/10.1016/j.tifs.2007.06.001
37. P. Chen, L. Yin, H. R. El-Seedi, X. Zou, and Z. Guo, *Food Chem.*, 2022, **394**, 133481. https://doi.org/10.1016/j.foodchem.2022.133481

38. Y. Tong, S. Wang, K. Han, X. Song, W. Zhang, Y. Ye, and X. Ren, *Food Anal. Methods*, 2021, **14**, 1590-1599. https://doi.org/10.1007/s12161-021-01999-1
39. J. Sun, X. Zhou, Y. G. Hu, X. H. Wu, X. D. Zhang, and P. Wang, Comput. *Electron. Agric*., 2019, **160**, 153-159. https://doi.org/10.1016/j.compag.2019.03.004
40. H. Jiang, H. Lin, J. Lin, S. Y. S. S. Adade, Q. Chen, Z. Xue, and C. Chan, *Food Control*, 2022, **133**, 108640. https://doi.org/10.1016/j.foodcont.2021.108640
41. K. Checa, M. Gamarra, J. Soto, W. Ipanaque, and G. L. Rosa, *IEEE CHILEAN Conf. Electr. Electron. Eng. Inf. Commun. Technol.*, 2019. https://doi.org/10.1109/CHILECON47746.2019.8987991
42. R. J. Shi, X. Z. Pan, C. K. Wang, Y. Liu, Y. L. Li, and Z. T. Li, *Spectrosc. Spect. Anal.*, 2015, **35**, 3140-3145. https://www.gpxygpfx.com/CN/abstract/abstract8037.shtml
43. Y. Y. Pu, Y. Z. Feng, and D. W. Sun, *Compr. Rev. Food Sci. Food Saf.*, 2015, **14**, 176-188. https://doi.org/10.1111/1541-4337.12123
44. J. H. Cheng, J. Sun, K. S. Yao, M. Xu, S. M. Wang, and L. H. Fu, *Spectrochim. Acta A*, 2022, **279**, 121479. https://doi.org/10.1016/j.saa.2022.121479
45. J. H. Cheng, J. Sun, K. S. Yao, M. Xu, and Y. Cao, *Spectrochim. Acta A*, 2022, **268**, 120652. https://doi.org/10.1016/j.saa.2021.120652
46. Y. Zhang, J. Sun, J. Li, X. Wu, and C. Dai, *Appl. Eng. Agric.*, 2018, **34**, 789-798. https://doi.org/10.13031/aea.12679
47. J. Sun, M. Wu, Y. Hang, B. Lu, X. Wu, and Q. Chen, *J. Food Process Eng.*, 2019, **42**, e13293. https://doi.org/10.1111/jfpe.13293
48. X. Zhou, J. Sun, Y. Tian, X. Wu, C. Dai, and B. Li, *J. Food Process Eng.*, 2019, **42**, e13085. https://doi.org/10.1111/jfpe.13085
49. X. Zhou, J. Sun, Y. Zhang, Y. Tian, K. Yao, and M. Xu, *J. Food Process Eng.*, 2021, **44**, e13897. https://doi.org/10.1111/jfpe.13897
50. J. Cheng, J. Sun, K. Yao, M. Xu, S. Wang, and L. Fu, *J. Sci. Food Agric.*, 2023, **103**, 2690-2699. https://doi.org/10.1002/jsfa.12376
51. S. Jun, Z. Xin, W. Xiaohong, L. Bing, D. Chunxia, and S. Jifeng, *Spectrochim. Acta A*, 2019, **212**, 215-221. https://doi.org/10.1016/j.saa.2018.12.051
52. S. Zeng, X. Wu, B. Wu, H. Zhou, and M. Wang, *Food Sci. Technol.*, 2023, **43**, e113422. https://doi.org/10.1590/fst.113422
53. X. Feng, H. Chen, Y. Chen, C. Zhang, X. Liu, H. Weng, S. Xiao, P. Nie, and Y. He, *Sci. Total Environ.*, 2019, **659**, 1021-1031. https://doi.org/10.1016/j.scitotenv.2018.12.458
54. T. Shen, C. Zhang, F. Liu, W. Wang, Y. Lu, R. Chen, and Y. He, *Sensors*, 2020, **20**, 13229. https://doi.org/10.3390/s20113229
55. A. Souza, M. Z. Rojas, Y. Yang, L. Lee, and L. Hoagland, *Heliyon*, 2022, **8**, e12256. https://doi.org/10.1016/j.heliyon.2022.e12256
56. J. Sun, Y. Cao, X. Zhou, M. Wu, Y. Sun, and Y. Hu, *J. Food Saf.*, 2021, **41**, e12866. https://doi.org/10.1111/jfs.12866
57. Y. Cao, J. Sun, K. Yao, M. Xu, N. Tang, and X. Zhou, *J. Food Process Eng.*, 2021, **44**, e13793. https://doi.org/10.1111/jfpe.13793
58. X. Zhou, C. Zhao, J. Sun, K. Yao, and M. Xu, *Spectrochim. Acta A*, 2023, **290**, 122288. https://doi.org/10.1016/j.saa.2022.122288
59. X. Zhou, Y. Liu, J. Sun, B. Li, and G. Xiao, *Sci. Total Environ.*, 2024, **949**, 175076. https://doi.org/10.1016/j.scitotenv.2024.175076
60. Q. Q. Han, K. M. Yang, W. Gao, Y. R. Li, and J. H. Zhang, *Environ. Sci. Pollut. Res.*, 2021, **40**, 35-43. https://doi.org/10.11654/jaes.2020-0860
61. J. Li, Z. Yang, Y. Zhao, and K. Yu, *Microchem. J.*, 2023, **194**, 109306. https://doi.org/10.1016/j.microc.2023.109306
62. L. Zhong, S. Yang, X. Chu, Z. Sun, and J. Li, *Sci. Total Environ.*, 2024, **907**, 168104. https://doi.org/10.1016/j.scitotenv.2023.168104
63. D. Lin, G. Li, Y. Zhu, H. Liu, L. Li, S. Fahad, X. Zhang, C. Wei, and Q. Jiao, *Comput. Electron. Agric.*, 2021, **187**, 106293. https://doi.org/10.1016/j.compag.2021.106293
64. L. Fu, J. Sun, S. Wang, M. Xu, K. Yao, and X. Zhou, *Spectrochim. Acta A*, 2022, **281**, 121641. https://doi.org/10.1016/j.saa.2022.121641
65. K. Yu, S. Fang, and Y. Zhao, *Spectrochim. Acta A*, 2021, **245**, 118917. https://doi.org/10.1016/j.saa.2020.118917
66. X. Zhou, J. Sun, Y. Tian, B. Lu, Y. Hang, and Q. Chen, *Food Chem.*, 2020, **321**, 126503. https://doi.org/10.1016/j.foodchem.2020.126503
67. J. Sun, B. Li, Y. Liu, Z. Wu, L. Shi, X. Zhou, P. Wu, and K. Yao, *Spectrochim. Acta A*, 2025, **340**, 126387. https://doi.org/10.1016/j.saa.2025.126387
68. J. Li, J. Ren, R. Cui, K. Yu, and Y. Zhao, *Front. Plant Sci.*, 2022, **13**, 1007991. https://doi.org/10.3389/fpls.2022.1007991
69. J. Zhang, M. Wang, K. Yang, B. Wu, Y. Li, Y. Li, and Q. Han, *IEEE Access*, 2022, **10**, 52258-52272. https://doi.org/10.1109/ACCESS.2022.3174690
70. Y. Lu, L. Nie, X. Guo, T. Pan, R. Chen, X. Liu, and F. Liu, *Ecotoxicol. Environ. Saf.*, 2024, **282**, 116704. https://doi.org/10.1016/j.ecoenv.2024.116704
71. R. Ullah, S. Khan, M. Bilal, F. Nurjis, and M. Saleem, *Optik*, 2016, **127**, 5186-5189. https://doi.org/10.1016/j.ijleo.2016.03.049
72. Y. Li, J. Sun, X. Wu, B. Lu, M. Wu, and C. Dai, *J. Food Sci.*, 2019, **84**, 2234-2241. https://doi.org/10.1111/1750-3841.14706
73. M. Saleem, H. Ali, M. Bilal, B. M. Atta, and N. Ahmad, *J. Fluoresc.*, 2023, **33**, 1695-1704. https://doi.org/10.1007/s10895-023-03185-4
74. X. Fu, and M. Wang, *Food Anal. Methods*, 2022, **15**, 115-123. https://doi.org/10.1007/s12161-021-02092-3
75. X. Zhou, C. Zhao, J. Sun, Y. Cao, and L. Fu, *Infrared Phys. Technol.*, 2021, **119**, 103936. https://doi.org/10.1016/j.infrared.2021.103936
76. X. Zhou, J. Sun, Y. Tian, K. Yao, and M. Xu, *Spectrochim. Acta A*, 2022, **266**, 120460. https://doi.org/10.1016/j.saa.2021.120460
77. X. Zhou, C. Zhao, J. Sun, Y. Cao, K. Yao, and M. Xu, *Food Chem.*, 2023, **409**, 135251. https://doi.org/10.1016/j.foodchem.2022.135251
78. X. Zhou, C. Zhao, J. Sun, J. Cheng, and M. Xu, *Spectrochim. Acta A*, 2024, **311**, 123991. https://doi.org/10.1016/j.saa.2024.123991
79. X. Zhou, C. Zhao, J. Sun, K. Yao, M. Xu, and J. Cheng, *Spectrochim. Acta A*, 2023, **291**, 122337. https://doi.org/10.1016/j.saa.2023.122337
80. L. Shi, J. Sun, S. Cong, X. Ji, K. Yao, B. Zhang, and X. Zhou, *Food Chem.*, 2025, **481**, 144055. https://doi.org/10.1016/j.foodchem.2025.144055
81. L. Shi, J. Sun, S. Cong, B. Zhang, X. Zhou, and X. Wu, *J. Food Compos. Anal.*, 2025, **147**, 108038. https://doi.org/10.1016/j.jfca.2025.108038
82. J. Liu, J. Sun, Y. Wang, X. Liu, Y. Zhang, and H. Fu, *Foods*, 2025, **14**, 2137. https://doi.org/10.3390/foods14122137
83. Z. Lun, X. Wu, J. Dong, and B. Wu, *Foods*, 2025, **14**, 2350. https://doi.org/10.3390/foods14132350
84. L. Shi, J. Sun, B. Zhang, Z. Wu, Y. Jia, K. Yao, and X. Zhou, *J. Food Compos. Anal.*, 2024, **135**, 106647. https://doi.org/10.1016/j.jfca.2024.106647

85. Z. Jiang, Z. Dong, W. Jiang, and Y. Yang, *Comput. Electron. Agric.*, 2021, **186**, 106184. https://doi.org/10.1016/j.compag.2021.106184

86. M. Yao, H. Yang, L. Huang, T. Chen, G. Rao, and M. Liu, *Appl. Opt.*, 2017, **56**, 4070-4075. https://doi.org/10.1364/AO.56.004070

87. Z. Yang, J. Ren, M. Du, Y. Zhao, and K. Yu, *Sensors*, 2022, **22**, 5679. https://doi.org/10.3390/s22155679

88. K. Yu, J. Ren, and Y. Zhao, *Artif. Intell. Agric.*, 2020, **4**, 127-139. https://doi.org/10.1016/j.aiia.2020.07.001

89. T. Lopes, R. Cavaco, D. Capela, F. Dias, J. Teixeira, C. S. Monteiro, A. Lima, D. Guimarães, P. A. S. Jorge, and N. A. Silva, *Talanta*, 2025, **283**, 127110. https://doi.org/10.1016/j.talanta.2024.127110

90. J. Aiswarya, K. Mariammal, V. S. Kumar, and K. Veerappan, *Optik*, 2025, **321**, 172183. https://doi.org/10.1016/j.ijleo.2024.172183

91. V. Adam, and J. Kaiser, *Int. J. Electrochem. Sci.*, 2013, **8**, 4485-4504. https://doi.org/10.1016/S1452-3981(23)14617-7

92. M. Galiová, J. Kaiser, K. Novotný, J. Novotný, T. Vaculovic, M. Liška, R. Malina, K. Stejskal, V. Adam, and R. Kizek, *Appl. Phys. A*, 2008, **93**, 917-922. https://doi.org/10.1007/s00339-008-4747-0

93. S. Krizkova, P. Ryant, O. Krystofova, V. Adam, M. Galiova, M. Beklova, P. Babula, J. Kaiser, K. Novotny, J. Novotny, M. Liška, R. Malina, J. Zehnalek, J. Hubalek, L. Havel, and R. Kizek, *Sensors*, 2008, **8**, 445-463. https://doi.org/10.3390/s8010445

94. M. Galiová, J. Kaiser, K. Novotný, M. Hartl, R. Kizek, and P. Babula, *Microsc. Res. Tech.*, 2011, **74**, 845-852. https://doi.org/10.1002/jemt.20967

95. E. R. Schenk, and J. R. Almirall, *Appl. Opt.*, 2010, **49**, C153-C160. https://doi.org/10.1364/AO.49.00C153

96. S. T. Shen, K. W. Kong, F. Liu, Z. H. Chen, J. D. Yao, W. Wang, and Y. He, *Molecules*, 2018, **23**, 2930. https://doi.org/10.3390/molecules23112930

97. W. Wang, W. Kong, T. Shen, Z. Man, W. Zhu, Y. He, and Y. Liu, *Front. Plant Sci*., 2020, **11**, 599616. https://doi.org/10.3389/fpls.2020.599616

98. F. Liu, L. Ye, J. Peng, K. Song, T. Shen, C. Zhang, and Y. He, *Sensors*, 2018, **18**, 705. https://doi.org/10.3390/s18030705

99. J. Peng, Y. He, J. Jiang, Z. Zhao, F. Zhou, and F. Liu, *Food Chem.*, 2019, **295**, 327-333. https://doi.org/10.1016/j.foodchem.2019.05.119

100. D. K. Tripathi, V. P. Singh, S. M. Prasad, N. K. Dubey, D. K. Chauhan, and A. K. Rai, *J. Photochem. Photobiol. B*, 2016, **154**, 89-98. https://doi.org/10.1016/j.jphotobiol.2015.11.008

101. J. Peng, F. Liu, F. Zhou, K. Song, C. Zhang, and L. Ye, *TrAC, Trends Anal. Chem.*, 2016, **85**, 260-272. https://doi.org/10.1016/j.trac.2016.08.015

102. H. C. Gutiérrez, C. Robles-Algarín, and A. Polo, *Processes*, 2025, **13**, 1688. https://doi.org/10.3390/pr13061688

103. L. Yang, L. Meng, H. Gao, J. Wang, C. Zhao, M. Guo, Y. He, and L. Huang, *Food Chem.*, 2021, **338**, 127886. https://doi.org/10.1016/j.foodchem.2020.127886

104. L. Huang, L. Meng, L. Yang, J. Wang, S. Li, Y. He, and D. Wu, *J. Anal. At. Spectrom.*, 2019, **34**, 460-468. https://doi.org/10.1039/c8ja00442k

105. H. T. Salloom, T. K. Hamad, and A. H. Mohammed, *J. Phys.: Conf. Ser.*, 2021, **1818**, 012178. https://doi.org/10.1088/1742-6596/1818/1/012178

106. Q. Zhao, Y. Yu, P. Cui, N. Hao, C. Liu, P. Miao, and Z. Li, *Spectrochim. Acta A*, 2023, **287**, 122053. https://doi.org/10.1016/j.saa.2022.122053

107. N. Fayek, W. Tawfik, A. KhalafAllah, and M. Fikry, *J. Opt.*, 2025. https://doi.org/10.1007/s12596-025-02524-x

108. Y. Zhao, and Q. Xie, Computers, 2025, **14**, 309. https://doi.org/10.3390/computers14080309

109. I. Goncharova, D. Guichaoua, S. Taboukhat, A. Tarbi, T. Chtouki, H. Erguig, and B. Sahraoui, *Spectrochim. Acta B*, 2024, **217**, 106943. https://doi.org/10.1016/j.sab.2024.106943

110. Z. Guo, P. Chen, N. Yosri, Q. Chen, H. R. Elseedi, X. Zou, and H. Yang, *Food Rev. Int.*, 2023, **39**, 1440-1461. https://doi.org/10.1080/87559129.2021.1934005

111. H. Jiang, Z. Wang, J. Deng, Z. Ding, and Q. Chen, *J. Food Sci.*, 2024, **89**, 8054-8065. https://doi.org/10.1111/1750-3841.17436

112. J. Wang, Q. Chen, T. Belwal, X. Lin, and Z. Luo, *Compr. Rev. Food Sci. F.*, 2021, **20**, 2476-2507. https://doi.org/10.1111/1541-4337.12741

113. L. Liu, X. Zeng, and J. Deng, *J. Phys.: Conf. Ser.*, 2021, **2030**, 012093. https://doi.org/10.1088/1742-6596/2030/1/012093

114. Z. Guo, P. Chen, L. Yin, M. Zuo, Q. Chen, H. R. El-Seedi, and X. Zou, *Food Control*, 2022, **132**, 108498. https://doi.org/10.1016/j.foodcont.2021.108498

115. M. M. Hassan, W. Ahmad, M. Zareef, Y. Rong, Y. Xu, T. Jiao, P. He, H. Li, and Q. Chen, *Food Chem.*, 2021, **358**, 129844. https://doi.org/10.1016/j.foodchem.2021.129844

116. J. Li, Z. Yang, Y. Zhao, and K. Yu, *Measurement*, 2024, **224**, 113911. https://doi.org/10.1016/j.measurement.2023.113911

117. J. Li, H. Guan, Y. Zhou, S. Pei, K. Yu, and Y. Zhao, *J. Agric. Food Chem.*, 2025, **73**, 10787-10798. https://doi.org/10.1021/acs.jafc.5c00126

118. A. O. Barimah, Z. Guo, A. A. Agyekum, C. Guo, P. Chen, H. R. El-Seedi, and Q. Chen, *Food Control*, 2021, **130**, 108341. https://doi.org/10.1016/j.foodcont.2021.108341

119. I. D. Juárez, T. Dou, S. Biswas, E. M. Septiningsih, and D. Kurouski, *Front. Plant Sci.*, 2024, **15**, 1371748. https://doi.org/10.3389/fpls.2024.1371748

120. H. Y. Wang, Z. J. Wu, L. X. Jiang, T. T. Jin, and Y. D. Liu, *Spectrosc. Spect. Anal.*, 2017, **37**, 1418-1423. https://www.gpxygpfx.com/CN/abstract/abstract9124.shtml

121. P. Chen, L. Yin, H. R. El-Seedi, X. Zou, and Z. Guo, *Food Chem.*, 2022, **394**, 133481. https://doi.org/10.1016/j.foodchem.2022.133481

122. Z. Yang, J. Li, L. Zuo, Y. Zhao, and K. Yu, *J. Anal. At. Spectrom.*, 2023, **38**, 2059-2072. https://doi.org/10.1039/d3ja00243h

123. J. Li, J. Ren, R. Cui, K. Yu, and Y. Zhao, *Front. Plant Sci.*, 2022, **13**, 1007991. https://doi.org/10.3389/fpls.2022.1007991

124. M. Yilmaz, A. Yilmaz, A. Karaman, F. Aysin, and O. Aksakal, *Talanta*, 2021, **225**, 121952. https://doi.org/10.1016/j.talanta.2020.121952

125. Q. Zuo, Y. Chen, Z. P. Chen, and R. Q. Yu, *Anal. Sci.*, 2018, **34**, 1405-1410. https://doi.org/10.2116/analsci.18P342

126. Z. Chen, and X. Wang, *Sci. Silvae Sin.*, 2020, **56**, 89-98. https://doi.org/10.11707/j.1001-7488.20200210

127. H. Yu, S. Xie, P. Liu, Z. Hua, C. Song, and P. Jing, *Remote Sens.*, 2023, **15**, 2299. https://doi.org/10.3390/rs15092299

128. L. Wang, Y. Zhou, J. Liu, Y. Liu, Q. Zuo, and Q. Li, *J. Clean. Prod.*, 2022, **367**, 132922. https://doi.org/10.1016/j.jclepro.2022.132922

129. J. Zhu, J. Deng, X. Zhao, L. Xu, and H. Jiang, *Microchem. J.*, 2024, **203**, 110946. https://doi.org/10.1016/j.microc.2024.110946

130. J. Zhu, J. Deng, X. Zhao, L. Xu, and H. Jiang, *Sens. Actuators A*, 2024, **368**, 115085. https://doi.org/10.1016/j.sna.2024.115085

131. W. Lu, H. Luo, L. He, W. Duan, Y. Tao, X. Wang, and S. Li, *Comput. Electron. Agric.*, 2022, **197**, 106923. https://doi.org/10.1016/j.compag.2022.106923

132. W. Zhou, J. Zhang, M. Zou, X. Liu, X. Du, Q. Wang, Y. Liu, Y. Liu, and J. Li, Environ. *Sci. Pollut. Res.*, 2019, **26**, 1848-1856. https://doi.org/10.1007/s11356-018-3745-9

133. L. Zhong, J. Qian, X. Chu, Z. Qian, M. Wang, and J. Li, *Trans. Chin. Soc. Agric. Eng.*, 2023, **39**, 265-270. https://doi.org/10.11975/j.issn.1002-6819.202207160

134. A. J. Da Silva, C. W. A. Do Nascimento, A. Da Silva Gouveia-Neto, and E. A. Da Silva Jr., *Water, Air, Soil Pollut.*, 2012, **223**, 3527-3533. https://doi.org/10.1007/s11270-012-1130-8

135. S. Sharma, and K. N. Uttam, *J. Appl. Spectrosc.*, 2018, **85**, 771-780. https://doi.org/10.1007/s10812-018-0717-2

136. C. Zhang, L. Zhou, Q. Xiao, X. Bai, B. Wu, N. Wu, Y. Zhao, J. Wang, and L. Feng, *Plant Phenomics*, 2022, **2022**, 9851096. https://doi.org/10.34133/2022/9851096

137. P. Fu, W. Zhang, K. Yang, and F. Meng, *Ecotoxicol. Environ. Saf.*, 2020, **206**, 111211. https://doi.org/10.1016/j.ecoenv.2020.111211

138. F. Li, L. Xu, T. You, and A. Lu, *Comput. Electron. Agric.*, 2021, **187**, 106257. https://doi.org/10.1016/j.compag.2021.106257

139. Y. Li, K. Yang, W. Gao, Q. Han, and J. Zhang, *Spectrochim. Acta A*, 2021, **255**, 119649. https://doi.org/10.1016/j.saa.2021.119649

140. X. Li, L. Li, and X. Liu, *Int. J. Appl. Earth Obs. Geoinf.*, 2019, **78**, 39-52. https://doi.org/10.1016/j.jag.2018.12.011

141. M. Liu, T. Wang, A. K. Skidmore, and X. Liu, *Sci. Total Environ.*, 2018, **637-638**, 18-29. https://doi.org/10.1016/j.scitotenv.2018.04.415

142. D. Sacristán, R. A. V. Rossel, and L. Recatalá, *Geoderma*, 2016, **265**, 6-11. https://doi.org/10.1016/j.geoderma.2015.11.008

143. Q. Liu, K. Sun, N. Zhao, J. Yang, Y. Zhang, C. Ma, L. Pan, and K. Tu, *Postharvest Biol. Technol.*, 2019, **153**, 152-160. https://doi.org/10.1016/j.postharvbio.2019.03.017

144. K. R. Borba, D. P. Aykas, M. I. Milani, L. A. Colnago, M. D. Ferreira, and L. E. Rodriguez-Saona, *Appl. Sci.*, 2021, **11**, 3209. https://doi.org/10.3390/app11073209

145. C. B. Fu, S. Cao, and A. H. Tian, *Sens. Mater.*, 2024, **36**, 5019-5029. https://doi.org/10.18494/SAM5199

146. S. Li, Y. Wang, W. Qin, X. Mo, B. Hu, and Y. Guo, *Trans. Chin. Soc. Agric. Mach.*, 2025, **56**, 451-457. https://doi.org/10.6041/j.issn.1000-1298.2025.03.044

147. A. Sanaeifar, F. Zhu, J. Sha, X. Li, Y. He, and Z. Zhan, *Sci. Total Environ.*, 2022, **802**, 149824. https://doi.org/10.1016/j.scitotenv.2021.149824

148. S. C. Dunagan, M. S. Gilmore, and J. C. Varekamp, *Environ. Pollut.*, 2007, **148**, 301-311. https://doi.org/10.1016/j.envpol.2006.10.023

149. A. Putra, M. Vassileva, R. Santo, and R. Tsenkova, *IOP Conf. Ser.: Mater. Sci. Eng.*, 2017, **210**, 012014. https://doi.org/10.1088/1757-899X/210/1/012014

150. Z. Wang, J. Deng, Z. Ding, and H. Jiang, *Infrared Phys. Technol.*, 2024, **138,** 105264. https://doi.org/10.1016/j.infrared.2024.105264

151. D. Xu, S. Chen, R. A. Viscarra Rossel, A. Biswas, S. Li, Y. Zhou, and Z. Shi, *Geoderma*, 2019, **352**, 61-69. https://doi.org/10.1016/j.geoderma.2019.05.036

152. Y. Chen, C. Zhang, C. Xiao, X. Zhao, Y. Shi, H. Yang, Z. Liu, and S. Li, *Acta Opt. Sin.*, 2020, **40**, 1030002. https://doi.org/10.3788/AOS202040.1030002

153. W. Yang, F. Li, Y. Zhao, X. Lu, S. Yang, and P. Zhu, *Anal. Methods*, 2022, **14**, 3944-3952. https://doi.org/10.1039/d2ay00593j

154. W. Yang, F. Li, S. Lyu, Q. Zhang, and Y. Zhao, *J. Anal. At. Spectrom.*, 2023, **38**, 1830-1840. https://doi.org/10.1039/d3ja00120b

155. X. F. Ni, C. B. Zhang, and X. Y. Tang, *Spectrosc. Spect. Anal.*, 2024, **44**, 2692-2700. https://www.gpxygpfx.com/CN/abstract/abstract14007.shtml

156. X. Ma, M. Z. Hua, C. Ji, J. Zhang, R. Shi, Y. Xiao, X. Liu, X. He, W. Zheng, and X. Lu, *Analyst*, 2022, **147**, 3628-3633. https://doi.org/10.1039/d2an00752e

157. J. Hao, F. Li, X. Jiang, Q. Wang, B. Yang, and J. Cao, *Spectrochim. Acta B*, 2023, **206**, 106711. https://doi.org/10.1016/j.sab.2023.106711

158. W. Q. Yang, Z. Q. Li, F. S. Li, S. B. Lu, and J. J. Fan, *Spectrosc. Spect. Anal.*, 2024, **44**, 670-674. https://www.gpxygpfx.com/article/2024/1000-0593-44-3-670.html#outline_anchor_1

159. S. Priya, and R. Ghosh, *Environ. Monit. Assess.*, 2023, **195**, 75. https://doi.org/10.1007/s10661-022-10739-9

160. K. Zhang, B. A. Kwadzokpui, S. Y. S. S. Adade, H. Lin, and Q. Chen, *Food Chem.*, 2024, **459**, 140305. https://doi.org/10.1016/j.foodchem.2024.140305

161. A. Murugesan, H. Li, and M. Shoaib, *Foods*, 2025, **14**, 2060. https://doi.org/10.3390/foods14122060

162. C. Wang, B. Wu, K. Jiang, M. Wei, and S. Wang, *Appl. Soil Ecol.*, 2019, **144**, 51-59. https://doi.org/10.1016/j.apsoil.2019.07.008

163. S. Wang, M. Wei, B. Wu, H. Cheng, and C. Wang, *Sci. Hortic.*, 2020, **261**, 108955. https://doi.org/10.1016/j.scienta.2019.108955

164. S. Ahmed, I. Razzaq, R. Sardar, M. N. Ahmad, T. Aziz, A. Shami, N. K. Alharbi, F. Al-Asmari, F. A. Al-Joufi, J. M. Alshammari, and L. Lin, *Ital. J. Food Sci.*, 2025, **37**, 276-294. https://doi.org/10.15586/ijfs.v37i2.2741

165. L. Jiang, M. M. Hassan, S. Ali, H. Li, R. Sheng, and Q. Chen, *Trends Food Sci. Technol.*, 2021, **112**, 225-240. https://doi.org/10.1016/j.tifs.2021.04.006

166. I. Ziani, H. Bouakline, A. El Guerraf, A. El Bachiri, M. L. Fauconnier, and F. Sher, *Trends Food Sci. Technol.*, 2025, **156**, 104850. https://doi.org/10.1016/j.tifs.2024.104850