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REVIEW ARTICLE

Spectral indices for monitoring soil heavy metal contamination: Direct soil and vegetation proxy approaches, current trends and future prospects

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Abstract

Soil heavy metal (HM) contamination is a critical environmental challenge with significant implications for ecosystem health, agricultural productivity and food security. Traditional laboratory-based monitoring methods are precise but costly and inefficient for large-scale, dynamic assessment. Consequently, remote sensing using spectral indices has emerged as a powerful, non-destructive alternative for detecting and mapping contamination. This review synthesizes the current science and applications of spectral indices for monitoring HM contamination in soils and vegetation. We explain the fundamental mechanisms underlying the spectral detection of metals, which primarily occur indirectly through metal-induced changes in soil physicochemical properties and plant physiological stress. The article categorizes and evaluates a range of vegetation-based, soil-based and emerging metal-specific indices, benchmarking their accuracy, transferability and sensitivity under diverse environmental conditions. A critical analysis identifies persistent challenges, including signal interference from soil moisture and organic matter, spectral overlap with other plant stressors and the lack of standardized, universally applicable indices. Finally, we highlight key future directions, emphasizing the integration of machine learning for intelligent index design, the fusion of optical data with thermal and radar sensors and the significant potential of next-generation spaceborne hyperspectral missions. It is concluded that the convergence of these advanced technologies could enable operational, global-scale monitoring networks, ultimately yielding valuable tools for evidence-based environmental management and remediation strategies.

Keywords: heavy metal contamination; hyperspectral; remote sensing; spectral indices

Introduction

Soil heavy metal (HM) contamination is a critical global environmental challenge, posing severe risks to ecological integrity, agricultural sustainability and public health (1, 2). This pervasive issue is primarily driven by intensified anthropogenic activities, including mining and smelting operations, which are major sources of cadmium (Cd), lead (Pb) and arsenic (As) (3) as well as industrialization, fossil fuel emissions and hazardous waste mismanagement (4). Furthermore, agricultural practices contribute significantly through the application of metal-enriched pesticides and phosphate fertilizers, elevating concentrations of copper (Cu) and zinc (Zn) (5). Urbanization also introduces contamination via vehicular emissions and atmospheric deposition, creating highly heterogeneous metal profiles in urban soils (6).

The persistence, toxicity and bioaccumulation potential of HM compound their environmental threat. They undergo complex biogeochemical transformations, remaining hazardous long after initial deposition. Their uptake by crops introduces them into the food chain, presenting serious food safety risks (7). Ecologically, HM disrupt soil microbial communities, impair nutrient cycling and cause plant chlorosis and reduced productivity. From a public health perspective, exposure, particularly in children is linked to neurological damage and carcinogenic effects (8). These multifaceted risks underscore the urgent need for comprehensive monitoring strategies.

However, effective monitoring is complicated by the inherent spatial heterogeneity of contamination, which is influenced by source intensity, landscape features and land use. For example, contamination often occurs in isolated hotspots of severe pollution within otherwise uncontaminated areas, such as those near industrial smelting sites, within agricultural fields with historic pesticide use, or along transportation corridors, making accurate risk assessment difficult (9). Conventional monitoring methods, such as Atomic Absorption Spectroscopy (AAS) and Inductively Coupled Plasma Mass Spectrometry (ICP-MS), provide precise analytical data but are inherently limited. They are costly, labour-intensive and time-consuming, requiring extensive sample preparation. Consequently, they yield only static, point-based snapshots that are inadequate for capturing spatial variability or dynamic changes at regional scales, thus hindering rapid response to emerging contamination events (10-12).

These limitations have catalysed the exploration of innovative, scalable alternatives. Remote and proximal sensing technologies have emerged as powerful tools for rapid, non-destructive, large-area assessment of soil properties (11). The fundamental premise is that HM stress induces detectable changes in the spectral reflectance of soils and vegetation. In plants, metal uptake triggers physiological and morphological changes, such as reduced chlorophyll content and altered cell structure, that manifest as specific spectral signatures, particularly in the visible and red-edge regions (13-15). In soils, metal ions interact with spectrally active constituents (e.g., organic matter, clay minerals, iron oxides), altering the soil's spectral shape and reflectance properties (11, 16).

Spectral indices are mathematical transformations of reflectance values at specific wavelengths designed to amplify subtle target signals and suppress background noise. They are crucial for enhancing the often-weak correlation between spectral data and trace metal concentrations (17, 18). Initially, general-purpose vegetation indices (VI) like the normalized difference vegetation index (NDVI) were adapted to detect metal-induced stress (19, 20). More recently, research has advanced toward developing specialized indices, such as the vegetation heavy metal pollution index (VHMPI), tailored explicitly for contamination response (21, 22).

This review provides a comprehensive synthesis of spectral index applications for monitoring soil HM contamination. Specifically, it (i) categorizes indices into vegetation-based, soil-based and metal-specific types, (ii) evaluates their performance across different sensing platforms and analytical approaches, (iii) critically examines existing challenges such as signal interference, transferability and lack of standardized indices and (iv) explores emerging trends including machine learning driven index design, multi sensor data fusion and the use of next-generation hyperspectral satellite missions. Beyond methodological aspects, the review also discusses broader implications for agricultural monitoring, food safety and environmental policy, positioning spectral indices as a cornerstone for large-scale contamination assessment.

Spectral science behind soil-metal interactions

The efficacy of spectral indices depends on understanding how metals interact with soil and vegetation to produce diagnostic spectral responses. This section delineates the spectral fingerprints generated by these interactions and elucidates the direct and indirect pathways through which they can be detected via reflectance spectroscopy.

Soil-metal spectral fingerprints

Heavy metals, typically present in trace concentrations, rarely produce direct absorption features in the visible (VIS), near-infrared (NIR), or shortwave-infrared (SWIR) regions due to their electronic structure (16, 23). Instead, their presence is detected indirectly through interactions with and alterations of, spectrally active soil constituents. These interactions manifest as modifications to the soil's spectral signature, forming the basis for direct detection approaches. The primary mechanism involves the adsorption of metal ions onto key soil components:

Organic matter (OM) complexation: Metals with a high affinity for OM-such as Cu and Pb form complexes with functional groups (e.g., carboxylic/phenolic OH). This binding alters the electron density and molecular conformation of OM, leading to measurable perturbations of its distinct SWIR absorption features (e.g., at 1730 nm, 2200 nm). These perturbations most commonly manifest as a decrease in absorption depth and a blue shift (shift toward shorter wavelengths) at ~2200 nm (24, 25). These interactions provide a fundamental basis for indirect metal monitoring using VIS-NIR-SWIR spectroscopy.

Adsorption onto iron oxides: When metals like Pb, Zn and cobalt (Co) adsorb onto iron oxide surfaces, they can modify the oxide's crystallinity, particle size and oxidation state. These alterations change the characteristic absorption depth and shape of the iron oxides' strong charge-transfer bands in the visible region (~500-900 nm) (26, 27).

Adsorption onto clay minerals: The adsorption of metals onto clay surfaces perturbs the vibrational features of structural hydroxyls (e.g., Al-OH at ~2200 nm, Mg-OH at ~2300 nm). The type of adsorption dictates the spectral change: cation exchange (e.g., with Cd^{2+}, Zn^{2+}) causes a weakening of absorption features, while inner-sphere complexation (e.g., with Pb^{2+}, Cu^{2+} on edge sites) leads to more pronounced alterations in the shape and depth of the Al-OH band (23, 26).

Consequently, while direct spectral signals from HM are weak, their presence is detectable through the alterations they cause to key soil constituents. These diagnostic changes manifest across specific wavelength ranges. In the visible (VIS, 400-700 nm), spectral variations are primarily driven by iron oxides and organic matter (OM). The near-infrared (NIR, 700-1400 nm) region is influenced by OM and water content. And in the shortwave infrared (SWIR, 1400-2500 nm) contains vibrational overtone and combination bands for clay minerals, carbonates and OM, which are highly sensitive to metal-induced compositional changes (18). Given the subtlety of these spectral alterations, advanced preprocessing techniques are essential to enhance weak signals and mitigate confounding factors like particle size and moisture. Methods such as Savitzky-Golay smoothing, First- and Second-Order Derivatives, Continuum Removal and Fractional-Order Derivatives (FOD) are routinely employed to highlight these features and improve the correlation with HM concentrations (18, 23, 28). Despite the weakness of direct metal signals, these alterations are the foundation of spectral monitoring. The following section explains how soil and vegetation fingerprints enable two primary remote sensing pathways for HM detection.

Direct vs indirect detection pathways

The spectral behavior of metals in the environment dictates two primary remote sensing detection pathways: direct sensing of soil reflectance and indirect sensing via vegetation proxies (Fig. 1).

Direct detection via soil reflectance: This pathway seeks to establish a quantitative relationship between the soil's spectral reflectance and its HM content (11, 29). However, this approach

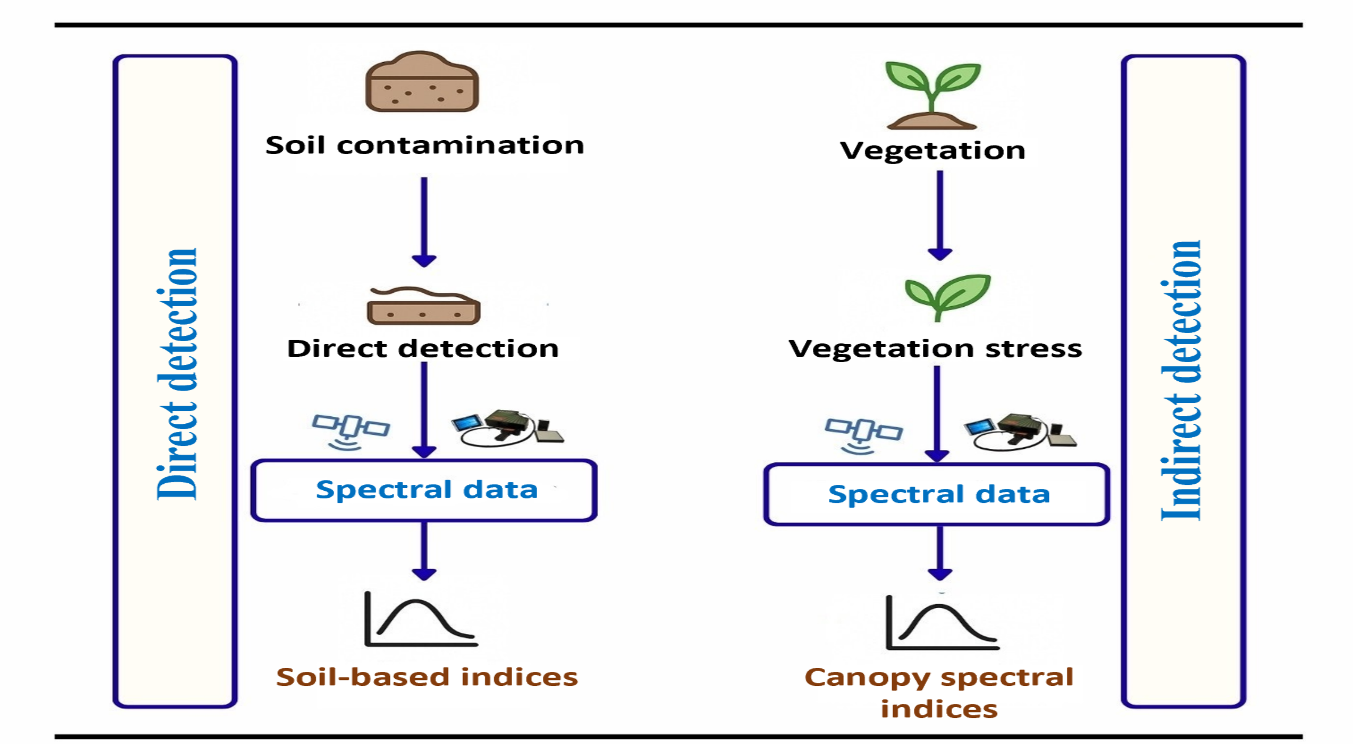


Fig. 1. Conceptual workflow of soil HM contamination detection through direct (soil-based) and indirect (vegetation stress) spectral indices.

faces significant challenges:

Weak and convolved signals: The spectral changes induced by trace metals are often obscured by the dominant influence of other soil properties, such as moisture, texture and inherent mineralogy (30).

High contamination threshold: Direct detection is most viable in areas of severe contamination (e.g., mining sites, smelteries), where metal concentrations are sufficiently high to cause discernible spectral shifts (16).

To overcome these limitations, research has focused on robust chemometric modelling applied to pre-processed spectra. Techniques such as partial least squares regression (PLSR) are favoured for their ability to handle multicollinearity in high-dimensional spectral data, while machine learning algorithms like random forests are particularly suited for deciphering the complex, non-linear relationships between reflectance and metal concentrations (18, 31). Controlled laboratory studies using spiked or artificially contaminated soil samples (near standard soil samples) have shown promise in isolating specific spectral response features for metals like Pb (32). Despite advances, direct detection remains challenging for typical field conditions, especially at low concentration levels.

Indirect detection via vegetation proxies: The indirect pathway capitalizes on the fact that plants bioaccumulate HM, which induces physiological stress that alters their spectral properties. This approach leverages vegetation as a bioindicator, transforming the plant canopy into a visible signal of subsurface contamination (20, 33). Heavy metal toxicity disrupts plant physiology through several mechanisms, each with a spectral manifestation:

Pigment degradation: Inhibition of chlorophyll synthesis and activity causes a decrease in absorption in the blue (~450 nm) and red (~670 nm) regions, leading to increased visible reflectance and a characteristic "blue shift" of the red-edge position (REP) toward shorter wavelengths (20, 34, 35).

Structural damage: Toxicity damages mesophyll cell structure, reducing light scattering and thereby lowering reflectance in the NIR plateau (700-1300 nm) (36).

Water stress: Impaired root function and water transport alter leaf water content, affecting absorption features in the NIR and SWIR regions centered around ~970, 1200 and 1450 nm (36).

The red-edge region (680-750 nm) is particularly sensitive and serves as a key indicator for early stress detection. The indirect pathway offers a powerful, non-destructive method for large-scale monitoring (20, 21). Its principal challenge is specificity: abiotic stressors like drought, nutrient deficiency and disease can elicit similar spectral responses, leading to potential false positives (37). Therefore, the effectiveness of vegetation-based detection depends on the plant species, the specific metal and the ability to disentangle co-factors through multi-index approaches or integration with soil data.

In practice, the choice between direct and indirect approaches depends on site conditions and available vegetation. Often, both pathways are used together to improve detection. In the following section, we examine various spectral indices that distil these soil and vegetation signals into contamination indicators.

Spectral indices as contamination indicators

Spectral indices, as mathematical transformations of reflectance data, help distil complex spectral information into actionable metrics for environmental monitoring. By emphasizing target features and minimizing background noise, they provide a cost-effective, rapid and non-destructive methodology for assessing HM contamination. This approach is applicable across multiple spatial scales, from high-resolution, proximal sensing of individual plants or soil samples, to field-scale surveys using handheld or unmanned aerial vehicle (UAV)-mounted sensors, up to landscape-level monitoring via airborne or satellite platforms (11, 12). This section critically reviews the development and application of these indices, categorizing them based on their primary target: vegetation canopies, bare soil and specific metal contaminants, as illustrated in Fig. 2.

Vegetation-based indices

Vegetation indices operate on the principle of indirect detection, leveraging plants as bioindicators. Heavy metal uptake induces physiological stress (38-40), manifesting as chlorosis, pigment degradation (41, 42) altered cellular structure (43, 44) and reduced water content (45). These biochemical changes cause measurable alterations in spectral reflectance, particularly in the visible (VIS) and near-infrared (NIR) regions (20).

Broad-band and general-purpose indices: Traditional indices like the NDVI are frequently employed as initial indicators of metal -induced vegetation vigour loss, often showing lower values in contaminated areas (2, 46). However, their lack of specificity is a significant limitation, as they respond similarly to drought, nutrient deficiency and other abiotic stressors (22). The photochemical reflectance index (PRI), designed for light-use efficiency, has shown notable sensitivity to metal stress (e.g., As) in some studies, though its performance can be seasonally dependent (11). Importantly, traditional broadband indices cannot distinguish metal stress from other causes of chlorosis, so they are generally used as broad indicators of plant health rather than specific metal biomarkers.

Red-edge indices: The red-edge region (~680-750 nm) is highly sensitive to subtle changes in chlorophyll content, making it critical for early stress detection. A characteristic "blue shift" (towards shorter wavelengths) of the red-edge position (REP) is a well-documented response to metals like Pb and As, caused by chlorophyll degradation (20). Consequently, red-edge chlorophyll indices (e.g., the chlorophyll index (red-edge) (CI red-edge) and the normalized difference red edge (NDRE) often provide greater sensitivity to metal-specific stress than broader greenness indices like NDVI (47).

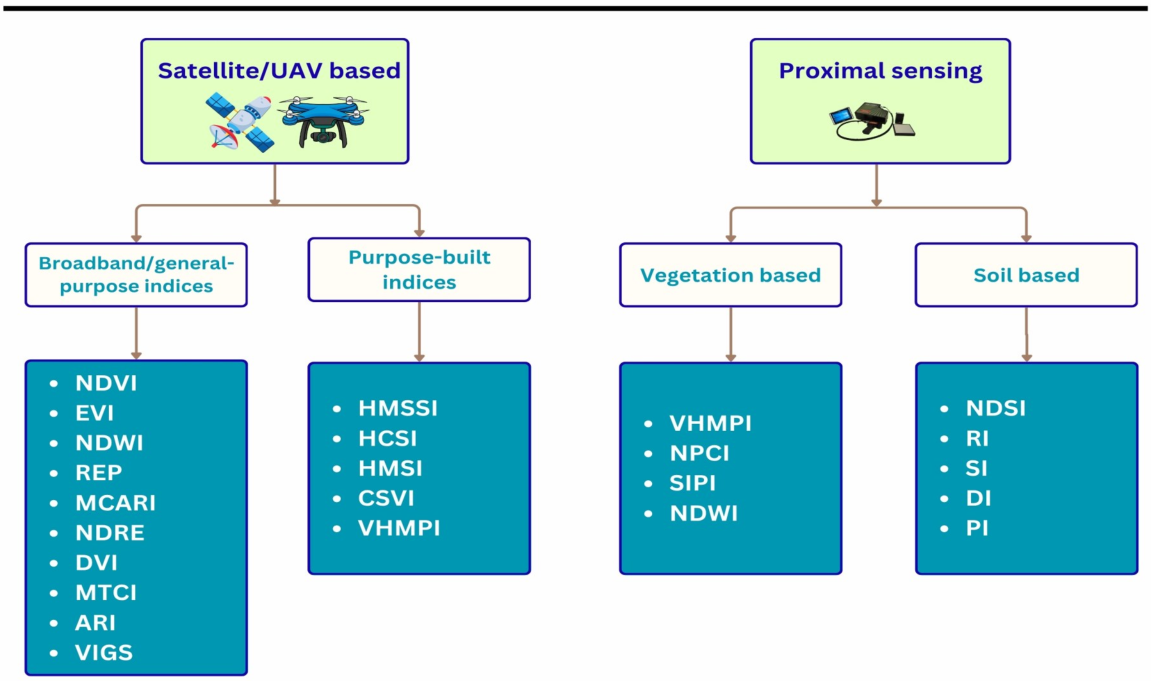
Purpose-built metal stress indices: To improve specificity, researchers have developed indices explicitly designed for HM contamination. These often combine signals from multiple physiological responses. Examples include:

Heavy metal stress sensitive index (HMSSI): Integrates chlorophyll and senescence metrics (chlorophyll index (red-edge) (CI red-edge)) and plant senescence reflectance index (PSRI)), outperforming its constituent indices in detecting stress in rice (47).

Cadmium (Cd) stress-sensitive spectral index (HCSI) and normalized heavy metal stress index (HMSI): These indices show strong correlations with Cd concentration and rice damage (48, 49).

Copper stress vegetation index (CSVI) and VHMPI: These utilize specific wavelength combinations to achieve stronger correlations with Co stress than general-purpose VIs (19, 22, 50).

Despite these advancements, a primary challenge remains differentiating metal-specific stress from other environmental pressures. This necessitates careful site-specific calibration and, where possible, integration with soil data or ancillary geospatial information. The formulas and primary applications for the indices discussed herein (e.g., NDVI, enhanced vegetation index (EVI) and PRI) are provided in Table 1. While vegetation indices are powerful for detecting canopy stress, their effectiveness depends on plant cover; areas with sparse



NDVI (Normalized Difference Vegetation Index), **EVI** (Enhanced Vegetation Index), **NDWI** (Normalized Difference Water Index), **REP** (Red Edge Position), **MCARI** (Modified Chlorophyll Absorption in Reflectance Index), **NDRE** (Normalized Difference Red Edge Index), **DVI** (Difference Vegetation Index), **MTCI** (MERIS Terrestrial Chlorophyll Index), **ARI** (Anthocyanin Reflectance Index), **VIGS** (Vegetation Index based on Green and SWIR), **HMSSI** (Heavy Metal Soil Stress Index), **HCSI** (Heavy Metal Concentration Stress Index), **HMSI** (Heavy Metal Stress Index), **CSVI** (Copper Stress Vegetation Index), **VHMPI** (Vegetation Heavy Metal Pollution Index), **VHMPI** (Vegetation Heavy Metal Pollution Index), **NPCI** (Normalized Pigment Chlorophyll Ratio Index), **SIPI** (Structure Intensive Pigment Index), **NDSI** (Normalized Difference Spectral Index), **RI** (Ratio Index), **SI** (Sum Index), **DI** (Difference Index), **PI** (Product Index).

Fig. 2. Classification of spectral indices for soil HM detection using satellite/UAV-based and proximal sensing approaches.

Table 1. Summary of common and specialized vegetation indices

Vegetation index	Formula	Application	References
NDVI (Normalized Difference Vegetation Index)	(NIR - Red) / (NIR + Red)	General vegetation health, biomass and vigor assessment.	(51)
EVI (Enhanced Vegetation Index)	G × (NIR - Red) / (NIR + C_1× Red - C_2 × Blue + L)	Improved vegetation monitoring reduces atmospheric and soil background influence.	(52)
OSAVI (Optimized Soil-Adjusted Vegetation Index)	(NIR - Red) / (NIR + Red + X) × (1 + X)	Vegetation monitoring with optimized soil background correction.	(53)
WDI (Water Deficit Index)	1 - (ET / ET_p)	Mapping plant water stress and evapotranspiration.	(54)
CSVI (Cu Stress Vegetation Index)	(R_{550} × R_{850}) / (R_{700}^2)	Specifically designed to detect Cu induced stress in vegetation.	(55)
NDRE (Normalized Difference Red Edge Index)	(NIR - Red Edge) / (NIR + Red Edge)	Sensitive to chlorophyll content and vegetation health in mid to late growth stages.	(56)
ARI (Anthocyanin Reflectance Index)	(1 / R_{550}) - (1 / R_{700})	Estimation of leaf anthocyanin content, a pigment linked to plant stress.	(57)
MTVI (Modified Triangular Vegetation Index)	1.2 × [1.2 × (R_{800} - R_{550}) - 2.5 × (R_{670} - R_{550})]	Estimation of leaf area index (LAI) while minimizing canopy background influence.	(58)
MCARI (Modified Chlorophyll Absorption in Reflectance Index)	[(R_{700} - R_{670}) - 0.2 × (R_{700} - R_{550})] × (R_{700} / R_{670})	Sensitive to chlorophyll concentration, it minimizes the effects of non-photosynthetic materials.	(59)
NDWI (Normalized Difference Water Index)	(NIR - SWIR) / (NIR + SWIR)	Estimation of vegetation water content.	(60)
SAVI (Soil-Adjusted Vegetation Index)	((NIR - Red) / (NIR + Red + L)) × (1 + L)	Vegetation monitoring that accounts for soil brightness variations.	(61)
NPCI (Normalized Pigment Chlorophyll Ratio Index)	(R_{680} - R_{430}) / (R_{680} + R_{430})	Indicator of pigment composition and chlorophyll/carotenoid ratio.	(62)

ET - Actual evapotranspiration; ET_p - Potential evapotranspiration; G, C_1, C_2, L, X - Empirical coefficients (as defined in formulas); R_{430}, R_{550}, R_{670}, R_{700}, R_{712}, R_{800}, R_{850} - Surface reflectance at respective wavelengths (nm).

vegetation may require soil-based approaches.

Soil-based indices: Bare-earth diagnostics

Direct detection of HM in bare soil via reflectance spectroscopy is inherently difficult due to their typically low concentrations and lack of direct spectral features in the VIS-NIR-SWIR range (23, 26). Therefore, soil-based indices rely on indirect detection by targeting spectrally active soil constituents that metals associate with, including OM iron oxides and clay minerals.

OM indices: Indices sensitive to the absorption features of OM (e.g., in the 500-600 nm and 1100-2500 nm regions) are used to infer enrichment of metals that complex strongly with OM, such as Cu and Hg. The utility of these proxies depends on the strength and exclusivity of the metal-OM relationship at a given site (30).

Iron oxide indices: Metals like Pb, Zn and Co often adsorb onto iron oxide surfaces. Since iron oxides have strong charge-transfer absorptions (e.g., ~500-900 nm), indices designed to capture their abundance and composition can be effective for indirect metal estimation (16, 23). For instance, the differential affinity of metals means an integrated approach is often necessary; for instance, while Cu correlations are often dominated by OM, Pb and Zn are frequently better estimated using iron oxide and clay indices (26).

Clay mineral indices: Indices targeting the characteristic absorption features of clay minerals in the SWIR region (~2200 nm and ~2300 nm) provide a pathway for detecting metal adsorption. quantifying perturbations to these features offers an indicator for associated metal contamination (16).

Optimized spectral indices: To enhance weak signals, researchers develop optimized indices like the normalized difference spectral index (NDSI) and the ratio spectral index (RSI) using identified sensitive wavelengths. For example, the Normalized Pigment Difference Index (NPDI) band 1417 and band 1246 was identified as a highly sensitive indicator for soil As (30). In general, multi-band indices are more robust than single- or two-band indices for representing the complex interactions between metals and soil constituents (26).

A significant constraint for soil-based diagnostics is the confounding effect of variable soil moisture, texture and surface roughness, which can mask or mimic metal-related spectral signals. Sophisticated preprocessing (e.g., continuum removal, derivative analysis) and statistical modelling are therefore essential to improve detection (48, 63). These soil-based strategies illustrate general approaches for detecting metal signals; in the next section, we explore emerging metal-specific indices designed to target particular contaminants.

Metal-specific indices: The emerging frontier

The ultimate goal in spectral index development is to move beyond general stress indicators toward indices with high specificity for individual metals. This emerging frontier focuses on identifying unique spectral response features linked to the biogeochemistry of specific contaminants. Examples include:

Copper (Cu): Tailored indices like the CSVI (using bands at 550, 700 and 850 nm) and the VHMPI (using 505, 640, 690 and 730 nm) demonstrate significantly stronger correlations with Cu stress than generic vegetation indices. This is supported by studies across various plant species; for example, sensitive regions have been identified near 505 nm, 640 nm, 690 nm and 730 nm in maize and near 550 nm, 700 nm and 800-900 nm in species like wheat, pea, locust and ash (19, 22).

Cadmium (Cd): Research has led to the development of Cd-sensitive indices such as HCSI. PLS-DA (Partial Least Squares Discriminant Analysis) models have successfully classified Cd contamination and studies have found significant correlations between indices like NDVI, the Carotenoid Reflectance Index (CRI), PRI2 (a variant of PRI) and extractable Cd in soils, highlighting the potential for quantitative assessment (20, 48, 55).

Lead (Pb) and zinc (Zn): The response to Pb often includes a notable blue shift in the REP. For both Pb and Zn, studies have identified optimal predictive wavelengths and vegetation indices based on pigment-related wavelengths have shown high correlation with leaf concentrations in species like *Rubus fruticosus* L. (20, 36).

The development of metal-specific indices is often facilitated by techniques like continuum removal, derivative analysis and the use of near-standard soil samples to isolate precise spectral feature bands (32). While promising, this field requires further validation across diverse plant species, soil types and contamination gradients to ensure robustness and generalizability. A summary of representative spaceborne and UAV-based studies focusing on HM stress detection in plants and soils is presented in Table 2.

Table 2. Summary of space-borne/ UAV sensing studies for HM stress detection in plants and soil

Target HM (s)	Plant species/ soil	Sensor/platform	Key vegetation index(s)	Key findings	References
Cd, Cu, Pb, Zn	Tropical forest	Landsat ETM+	VIGS, NDVI	VIGS outperformed NDVI in detecting metal-induced stress. High VIGS anomalies correlated with elevated soil metal content associated with specific geological formations.	(21)
Cu	General vegetation (mining area)	Hyperion (Hyperspectral)	CSVI = $(R_{550}/R_{850}) \times (R_{700}/R_{850})$	CSVI showed a significant positive correlation with Cu content ($r > 0.7$). Effective for mapping Cu stress near mining zones.	(22)
Cd	Rice (agricultural region)	Sentinel-2	NDRE	NDRE was a sensitive stress indicator; the Bayesian model achieved 81.57 % accuracy in identifying Cd-specific stress using its stable temporal signature.	(48)
Cd	Basil, kale (controlled lab)	Hyperspectral Imaging (HSI) Camera	ARI = $(1/R_{550})$ - $(1/R_{700})$ (+ 14 others)	ARI detected all Cd stress levels, outperforming NDVI due to sensitivity to photoprotective pigments.	(64)
Cd, Cu, Pb, Zn	General vegetation (anthropogenic area)	Landsat ETM+	NDVI, NDVI anomalies	NDVI anomalies negatively correlated with soil magnetic susceptibility, serving as a low-cost screening tool for polluted/degraded zones.	(65)
Cd	Rice (contaminated area)	Sentinel-2	HMSI (from Cab-LAI feature space)	Inverted chlorophyll (Cab) and LAI were combined to form HMSI ($r = 0.84$ with soil Cd), effectively mapping stress over large areas.	(66)
Cd, Pb, Hg, As	Rice (effluent-irrigated fields)	FLIR SC660 thermal imager + Landsat 8 OLI	HMSI (canopy T + LAI)	Integration of canopy temperature (physiological response) and LAI into HMSI enabled early HM stress detection.	(49)
Fe	General vegetation (mining areas)	HyMap, Hyperion	WDI, VII	WDI using water-absorption features effectively identified Fe-rich areas and monitored vegetation in mining regions.	(67)
Cd, Pb, As	Rice (field)	HJ-1A/B CCD	EVI	Heavy metal stress caused slower growth and shorter phenological periods. Time-integrated EVI was a good metric for differentiating stress levels.	(68)
Cd	Rice (field)	Landsat 7 ETM+ & Landsat 8 OLI	NDVI time-series	A feature space combining phenological and simulated root-biomass indicators distinguished severe stress (>95 % accuracy).	(69)
Cd, Pb	Rice leaves (lab)	Field UniSpec spectrometer	NDVI, CRI, PRI2, NPCI	Hyperspectral data estimated bioavailable Cd ($R^2 = 0.59$) but not Pb, due to Cd's higher mobility and plant uptake.	(55)
Cd	Rice (field)	ASD FieldSpec & Sentinel-2A	HCSI = $(R_{780} - R_{712})/R_{678} \times (R_{678}/R_{550})$	HCSI, based on chlorophyll sensitivity, detected Cd stress with high correlation ($r = 0.85$-0.95) and clear stress-level separation.	(70)
Cd, Cu	General vegetation (mining sites)	AVIRIS-NG & Field Spectrometer	CSVI, HMSSI, ARI-1, NDVI	Combined indices (CSVI, HMSSI, ARI-1) were more effective (AUC = 0.69) than single-index methods for mapping mining-induced stress.	(71)
Cd, Cr, Cu, Ni, Pb, Zn	General vegetation (mining areas)	MODIS & Sentinel-2A	NDVI, MTCI	MTCI strongly correlated with chlorophyll content ($r = 0.96$), effectively indicating stress; NDVI showed lower sensitivity.	(20)
Cd, Pb, Hg	Rice (paddy fields)	Fused Landsat	EVI, NDWI	A Growth Rate Fluctuation Index (GRFI) derived from EVI/NDWI temporal profiles was a stable and sensitive stress indicator.	(72)
Pb, Cd, As	Rice (polluted area)	HJ-1A HSI & Radarsat-2 SAR	NVI (optical), SVI (SAR)	Fusing optical (chlorophyll) and microwave (biomass) indices improved stress-classification accuracy (82 %).	(73)
Cd	Rice (mining area)	Sentinel-2A	REP, CIred-edge, MSR, MCARI, NDRE	A GRU deep-learning model using red-edge time-series achieved 93.5 % accuracy in detecting regional HM stress.	(74)
HM	Rice (regional)	Sentinel-2A + WOFOST model	SIST (LAI & NDVI-based)	A Stress Index (SIST) derived from LAI spatio-temporal dissimilarity effectively identified HM stress clusters.	(75)
Cd, Pb, Hg	Rice (contaminated river area)	Sentinel-2	HMSSI = CIred-edge / PSRI	HMSSI outperformed single indices (< 20 % vs. > 60 % misjudgement). Multitemporal models across growth stages gave the highest accuracy.	(47)
Cu, Pb and As	Daxigou mining area, China (Soil)	Landsat 8 OLI + DEM	NDVI, DVI, CMR, EVI	Integrating RS indices with DEM and a GA-BP neural network improved topsoil HM estimation accuracy.	(76)

r - Pearson's correlation coefficient; R^2 - Coefficient of determination; AUC - Area under curve; GA-BP - Genetic-Algorithm Back-Propagation neural network; GRU - Gated Recurrent Unit.

Sensors and platforms driving index development

The effective application of spectral indices is intrinsically linked to the capabilities of the sensing platforms from which they are derived. The choice of platform, ranging from laboratory spectrometers to satellite constellations, dictates the spectral, spatial and temporal resolution of the data, thereby influencing the type of indices that can be developed and their respective applications. This section examines the roles of hyperspectral, multispectral and proximal sensing technologies in advancing the field of heavy metal monitoring.

Hyperspectral imaging (HSI)

HSI sensors capture reflectance data across hundreds of narrow, contiguous spectral bands, providing a near-continuous spectrum for each pixel. This rich spectral resolution is paramount for detecting the subtle and often overlapping spectral signatures induced by HM stress in both soils and vegetation (11, 13).

The primary strength of HSI lies in its ability to identify specific narrow-band features and develop sensitive, purpose-built indices. For instance, the CSVI was successfully applied to spaceborne Hyperion imagery, enabling mapping of Cu stress at a landscape scale (55). Airborne HSI has been effectively used to map the spatial distribution of various metals (e.g., Cr, Cu, Ni, Zn) in leaves of pioneer species on industrial brownfields and to estimate pollution in agricultural soils using advanced machine learning algorithms like Random Forest (77, 78). These studies illustrate HSI's utility in HM mapping.

However, the use of HSI comes with inherent challenges. The high dimensionality of the data introduces redundancy and increases susceptibility to noise, necessitating sophisticated preprocessing and feature selection techniques (13, 18). Furthermore, operational use is often constrained by factors such as weather sensitivity, the need for complex atmospheric correction and the computational burden of processing large datasets (79).

Multispectral remote sensing

In contrast to HSIs, multispectral instruments operate with a limited number of broad spectral bands. Historically, this has limited their utility for direct HM detection. However, the launch of new-generation satellites with enhanced capabilities has revolutionized their role. For example, the European Sentinel-2 satellites include dedicated red-edge bands, providing significantly improved capacity for assessing vegetation health and stress (48). In general, multispectral platforms offer frequent, synoptic coverage over large areas at low cost, enabling long-term monitoring and time-series analysis. This is invaluable for tracking contamination dynamics and evaluating remediation efforts (65). For instance, MODIS (Moderate Resolution Imaging Spectroradiometer) NDVI time series have been used to assess vegetation changes in mining areas, while phenological indicators derived from HJ-1A/B CCD (Huan-Jin -1A/B Charge-Coupled Device) images have monitored HM stress in crops (20, 68). Broad-band indices like the Vegetation Index considering Greenness and Shortwave Infrared (VIGS), developed from Landsat ETM+ (Enhanced Thematic Mapper Plus) data, demonstrate potential for mapping vegetation anomalies related to mineral deposits (21). These examples illustrate the ability of multispectral sensors to provide large-scale observations; however, their use requires careful calibration and data processing.

A key limitation remains the lack of specificity of broadband indices, as they respond to a wide range of stressors beyond HM (21, 22). Their application is also most effective in arid and semi-arid regions where vegetation cover is sparse, minimizing the obscuration of soil signals (21). Data quality can be compromised by atmospheric conditions, requiring robust correction methods (79). Consequently, while multispectral systems enable broad coverage and frequent monitoring, their indices often serve as general plant health indicators rather than specific metal detectors. The data from these platforms must therefore be carefully processed and interpreted and broadband vegetation indices (e.g., NDVI, EVI) tend to reflect overall plant stress rather than metal-specific effects (21, 22).

Proximal sensing

Proximal sensing conducted using portable field spectroradiometers (e.g., ASD Field Spec, SVC HR-1024) at close range, serves as the fundamental basis for spectral index development. By providing high-fidelity, laboratory-quality spectra under controlled conditions, proximal sensing allows for precise identification of key wavelength regions and the development of sensitive indices before they are adapted for airborne or satellite use (23, 28). This approach is critical for establishing the fundamental relationships between HM concentration and spectral response. Studies using proximal sensing have been instrumental in pinpointing sensitive wavelengths:

- The visible region (400-700 nm) and red-edge (680-750 nm) are highly responsive to metal-induced chlorophyll degradation and pigment changes, often manifesting as the characteristic blue shift of the red-edge position (80, 81).
- The near-infrared region (NIR, 700-1300 nm) is sensitive to mesophyll structural alterations caused by metal toxicity, making this spectral region a key indicator for stress damage study.
- The shortwave-infrared (SWIR, 1400-2400 nm) region is sensitive to vegetation water stress and provides information on soil composition, most notably the spectral signatures of specific clay minerals (e.g., smectite, kaolinite), carbonates and sulphates (21).

Proximal sensing is rapid, economical and excellent for diagnosing subtle biochemical changes (36). Its main challenges are the inherently weak direct spectral signals of metals in soil and the "transferability gap," where models calibrated under controlled laboratory conditions may not perform robustly in complex natural environments due to confounding factors like moisture, texture and variable illumination (23). Thus, proximal studies are essential for index development but must be validated under field conditions to ensure operational reliability. A synthesis of proximal sensing studies addressing HM stress detection in plants is provided in Table 3 and 4.

Benchmarking spectral indices for metal monitoring

The development of a spectral index is only the first step; its true utility is determined by rigorous benchmarking across diverse environments. This section critically evaluates index performance, focusing on the central trade-off between accuracy and transferability, their behaviour across varying conditions and strategies to account for confounding soil properties.

Table 3. Summary of proximal sensing studies for HM stress detection in plants

Target HM(s)	Study context	Plant species	Sensor	Vegetation index (VI)	Statistical model	Data pre-processing	Key findings	References
Cu	Greenhouse experiment, Beijing, China	*Zea mays* (maize) leaves	SVC HR-1024I spectroradiometer	VHMPI (vegetation heavy metal pollution index, proposed), WBI, PSNDa, PRI, NDVI	Pearson correlation, F-test	First-order derivative (D), Continuum removal (CR)	The proposed VHMPI showed a strong correlation with Cu^{2+} stress (r = -0.8757 in 2016; r = -0.8772 in 2017), surpassing traditional VIs across varieties and growth stages.	(22)
Cu, Ni	Controlled greenhouse pot experiment, Cu/ Ni-spiked soil	*Triticum aestivum* (spring wheat) leaves	ASD FieldSpec 3 Pro spectrometer	NPCI, NDWI, SIPI, RVSI, red-edge position indices	Pearson correlation, Spectral Angle Mapping (SAM)	First-order derivative (D1), Continuum Removal (CR)	NPCI performed best for Ni stress (r = 0.712, p < 0.05), while NDWI correlated most with Cu (r = -0.711, p < 0.01). A distinct blue shift in red-edge position under Cu stress was observed. VI sensitivity varied by growth stage.	(63)
As, Cr, Zn, Cu, Cd, Pb	Polluted vs. uncontaminated rice farmlands, Northeast China	*Oryza sativa* (rice) canopy and leaves	ASD FieldSpec 3 spectrometer	X24, NI10, WI2, NRG, SDg/SDr and 66 chlorophyll-related indices	Correlation analysis, Spectral Index Space modeling	First- & second-derivative spectra, Continuum Removal (CR)	Chlorophyll indices were negatively correlated with HM stress (R^2 = 0.72 via 2nd-derivative spectra). A 3D spectral index space (NI10 for N, WI2 for water, chlorophyll VI) classified stress levels more effectively than single-VI methods.	(82)

Table 4. Key spectral indices for HM detection in soils

Index name	Acronym	Formula	Key application	Target HM(s)	References
Normalized Difference Index/ NDSI	NDI/ NDSI	$(R_\alpha - R_\beta) / (R_\alpha + R_\beta)$	Best performer for Ni in low-pollution areas. Highly sensitive indicator for As in low organic matter soils.	Ni, As, Pb	(23, 30, 32)
Ratio Index	RI	R_α / R_β	Used for identifying spectral response features for Pb. Effective for various HMs, often used alongside NDIs.	Ni, Co, Fe	(28, 83)
Difference Index	DI	$R_\alpha - R_\beta$	Highlighting absorption features for Mn in saline-alkali soils.	Mn	(28)
Product Index	PI	$R_\alpha * R_\beta$	Used in comparative studies, though often outperformed by NDI/RI.	Ni	(83)
Sum Index	SI	$R_\alpha + R_\beta$	Used in comparative studies for HM assessment.	Ni	(83)
Three-Band Index	TBI	$(R_\alpha - R_\beta)/R_c$	Magnifying subtle Cr signals; effective for multiple HMs (Pb, Zn, Mn, As).	Cr, Pb, Zn, Mn, As	(16, 84)

*R_α: Reflectance at a specific wavelength (λa), R_β: Reflectance at a different wavelength (λb) and R_c: Reflectance at a third wavelength (λc).

Accuracy vs transferability

A pervasive challenge in spectral monitoring is the tension between achieving high accuracy in a specific, controlled context and maintaining robust performance across different geographical and environmental settings. Indices are often developed through regression on limited datasets, leading to models that can be overfit to local conditions (22). Purpose-built indices like the CSVI and the VHMPI can show remarkable accuracy in their original studies, but their transferability is frequently limited. For example, CSVI was effective only in areas with high vegetation cover (85) and VHMPI, originating from laboratory leaf-scale studies, requires validation at field and image scales (3). Furthermore, the spectral response features for soil metals can vary significantly between sites, making it difficult to attribute specific bands to a metal rather than to a mixture of soil properties (32).

The choice of data processing techniques also impacts transferability. Integer-order spectral derivatives may overlook subtle information, whereas refined methods like FOD show promise for better generalization by extracting a broader range of spectral features (18, 23). However, the optimal parameters for these transformations are often context-dependent (86). Despite these challenges, some indices demonstrate inherent robustness. Indices like the EVI and Soil-Adjusted Vegetation Index (SAVI), which build upon the NDVI formula with corrective terms, demonstrate significantly improved stability across varying measurement conditions and soil backgrounds, enhancing their utility for large-scale monitoring (33). Balancing index sensitivity with generalizability thus requires careful algorithm design and extensive cross-validation.

Cross-comparisons across soil types and land covers

The performance of spectral indices is highly contingent on environmental context. The applicability of soil-based indices is often restricted to arid and semi-arid regions where sparse vegetation exposes the soil surface, as thick canopy cover obscures underlying contamination signals (21). Even within vegetated areas, index performance varies. For instance, the VIGS showed consistent patterns across different geological units, suggesting robustness against variations in parent material (21). In contrast, optimal index combinations and model parameters for HM estimation are often highly specific to land cover type, such as entisols in mining areas or saline-alkali soils (28, 84).

The plant species itself is a critical factor. Different species exhibit diverse physiochemical responses to metal stress (e.g., maize under Zn, Pb and Cr stress), meaning generic indices may fail to capture specific stress mechanisms (37). This has driven the development of specialized indices, such as the HMSSI for rice, which leverages Sentinel-2 red-edge bands to improve accuracy for that specific crop (47). Consequently, there is a growing emphasis on developing metal- and species-specific indices that can be applied consistently across datasets (15). Overall, these studies highlight that environmental and biological context strongly affect index performance, motivating approaches that incorporate species and land-cover information.

Linking indices with soil physicochemical properties

The indirect nature of HM detection means that spectral indices often measure the effect of metals on spectrally active soil constituents, rather than the metals themselves. This creates a strong confounding effect, as key soil properties like organic matter (OM), iron oxide content, clay minerals, pH and moisture co-vary with metal concentrations and dominate the spectral response (16, 84). For instance, the correlation between Cu and reflectance is primarily influenced by OM, while Pb, Zn, Co and Ni are largely associated with clay minerals and iron-manganese oxides (16). Therefore, most soil monitoring strategies are inherently indirect, leveraging indices designed to capture these proxy signals (e.g., indices for OM or iron oxides) to estimate metal loads (23, 30).

Advanced spectral processing techniques are essential to disentangle these complex effects. Methods such as continuum removal and first- and second-order derivatives are crucial for enhancing subtle absorption features and significantly increasing the correlation between spectra and metal content (16, 86). Multivariate regression methods like PLSR are widely used to model these complex, collinear relationships (31).

A promising frontier is multi-source data integration. Fusing optical hyperspectral data with microwave Synthetic Aperture Radar (SAR) data can provide a more comprehensive view by capturing both biochemical changes (via optical sensors) and morphological or biomass changes (via SAR) (87). Similarly, integrating proximal sensing data with ancillary soil attributes (e.g., OM, pH) in a feature-space analysis can significantly improve estimation accuracy for spectrally inactive elements like chromium (16). These multi-modal strategies suggest pathways to mitigate confounding soil effects by providing complementary information.

Critical challenges and knowledge gaps

Despite significant advances, the development and application of spectral indices for HM monitoring face persistent challenges that limit their operational robustness. This section delineates the foremost technical and methodological hurdles that must be addressed to transition from research to widespread practical application.

Signal interference: Soil texture, moisture and organic matter

The most fundamental challenge for direct soil monitoring is the inherently weak and often featureless spectral response of HM at typical environmental concentrations in the visible and near-infrared (VIS-NIR) regions (88, 89). This feeble signal is overwhelmingly dominated by the strong absorption features of spectrally active soil constituents, primarily OM, clay minerals and iron oxides (69). Heavy metals readily bind to these components, meaning their detection is almost always indirect, inferred through spectral changes in these proxies rather than via direct metal signatures (30). This creates a widespread spectral confounding effect, where variations in OM or clay content can mask or mimic the spectral signal of metal contamination (32). Dynamic soil properties like moisture and temperature introduce significant noise and variability, further complicating the isolation of a stable metal-specific signal (12, 28). While advanced preprocessing techniques aim to mitigate these effects, their effectiveness remains limited in highly complex and heterogeneous natural environments (18). These issues highlight why direct soil-based index application remains challenging without additional soil property information.

Vegetation complexity: Stress overlap beyond metals

Indirect detection via vegetation stress is confounded by a lack of specificity. Heavy metal toxicity induces physiological responses, including chlorophyll degradation, altered cellular structure and water stress that manifest as spectral changes in the visible, red-edge and shortwave-infrared regions (20). However, these responses are spectrally similar to those caused by other abiotic stressors such as drought, nutrient deficiency, pests and disease (49). Consequently, vegetation indices often function as general indicators of plant health rather than specific biomarkers for metal stress. The subtle spectral signatures of metal toxicity can be easily overwhelmed by more pronounced changes driven by factors like water availability or fertilization (82). This spectral overlap makes accurate differentiation and attribution of stress causation exceptionally difficult using optical data alone, leading to a high potential for false positives. Thus, while vegetation indices are useful for flagging stressed areas, additional data or methods are needed to distinguish metal stress from other factors.

Index saturation and sensitivity limits

Spectral indices face inherent limitations at both ends of the contamination spectrum. At low or trace concentrations, HM are often spectrally indistinguishable from background soil or plant variability, falling below the detection limit of conventional VIS-NIR spectroscopy (83). Conversely, at high levels of contamination or dense vegetation cover, many broad-band indices (e.g., NDVI) saturate, losing sensitivity to further increases in metal concentration or subtle physiological changes (21, 22). While hyperspectral sensing offers increased sensitivity through narrow-band indices targeting specific regions like the red-edge, it introduces challenges of data redundancy and computational complexity, making precise band selection and model tuning paramount (90). Ultimately, the performance of any index is highly contingent on the specific metal, its concentration, the plant species and the environmental context, hindering the establishment of universal detection thresholds (36). This limitation calls for the development of tailored indices or adaptive models that account for these factors.

Lack of standardized metal-specific indices

A critical knowledge gap is the absence of universally validated metal-specific indices. Most vegetation indices in use (e.g., PRI, NDVI) were designed for general purposes like assessing photosynthetic efficiency or biomass, not for diagnosing HM stress (22). Their application to metal monitoring is therefore often correlative and lacks a robust mechanistic basis. Although novel purpose-built indices like CSVI and VHMPI show promise, they are typically developed from limited datasets. Consequently, they often lack extensive validation across diverse environmental conditions, plant species and metal types (3). This has led to a literature in which identified "feature bands" vary significantly between studies, preventing consensus and standardization (32).

Addressing this gap requires a multi-faceted approach: (i) conducting controlled studies using "near standard soil samples" to isolate fundamental metal-specific spectral responses (55) (ii) integrating multi-source data (e.g., optical hyperspectral with SAR) to create multi-dimensional feature spaces that capture a wider range of stress symptoms (73) (iii) adopting advanced modelling techniques like machine learning and radiative transfer models to disentangle the complex interplay of factors influencing spectral data (16, 18). By systematically combining laboratory, field and remote sensing data, researchers can move toward standardized, metal-specific indices that are robust and broadly applicable.

Emerging trends and future directions

The field of spectral index development for HM monitoring is undergoing rapid transformation, driven by advances in computational power, sensor technology and data fusion methodologies. These innovations promise to overcome longstanding challenges and transition from localized research to global, operational monitoring systems.

Machine learning enhanced index design

The complexity of spectral responses to HM stress, often confounded by environmental variables such as soil moisture, crop growth stage, atmospheric conditions and nutrient status, necessitates a move beyond traditional empirical indices. ML (Machine Learning) and AI (Artificial Intelligence) are revolutionizing index design by autonomously identifying optimal spectral bands and modeling the complex, non-linear relationships between spectral data and metal concentrations. Techniques like FOD preprocessing, combined with optimal band selection algorithms, can highlight subtle, hidden spectral information and effectively suppress noise, significantly improving estimation accuracy for elements like Hg, Cr and Cu (18). Feature selection methods such as Monte Carlo Uninformative Variable Elimination (MC-UVE) precisely identify the most responsive spectral bands for specific metals, enhancing model robustness (55).

Advanced regression models, including PLSR, Random Forest Regression (RFR) and Convolutional Neural Networks (CNN) have demonstrated superior performance compared to conventional techniques. These models capture intricate spectral-metal relationships, with studies demonstrating the superior predictive performance of algorithms like CatBoost for estimating Zn, Mn, As and Pb (31, 84). The future lies in developing explainable AI (XAI) frameworks that not only deliver high accuracy but also provide transparent, interpretable insights into the mechanistic basis of the selected spectral features. These ML-based approaches promise more reliable detection, though their success will depend on the availability of diverse training data and careful validation.

Fusion with thermal and radar data

No single sensor can capture the full spectrum of plant physiological responses to metal stress. Multi-sensor data fusion leverages complementary information to provide a more holistic diagnostic framework. The synergy between optical hyperspectral data and microwave SAR is particularly powerful. Optical sensors are adept at detecting biochemical changes (e.g., chlorophyll content), whereas SAR is sensitive to morphological characteristics like plant structure and biomass. The fusion of these complementary data types has been shown to significantly improve the accuracy of monitoring HM stress in rice, as it constructs multi-dimensional feature spaces that better discriminate stress levels (73). This approach is especially valuable in perennially cloudy regions where optical data alone is insufficient.

Thermal infrared sensing adds another critical dimension by monitoring canopy temperature, a key indicator of plant physiological function that often responds to metal toxicity earlier than visual symptoms appear. Integrating canopy-air temperature models with Leaf Area Index (LAI) data from optical sensors provides a reliable method for evaluating stress levels. Multi-temporal thermal data, for example, can highlight periods of thermal stress that correlate with metal uptake (49, 91). By broadening data sources, fusion enables more resilient detection of contamination. In essence, the fusion of optical, SAR and thermal data offers a multi-faceted view of plant-soil systems, capturing both biochemical and physical responses to contamination.

Next-generation spaceborne hyperspectral missions

The ongoing revolution in spaceborne hyperspectral imaging is set to overcome traditional data cost and availability barriers. New and upcoming missions such as PRecursore IperSpettrale della Missione Applicativa (PRISMA), Environmental Mapping and Analysis Program (EnMAP) and the future Surface Biology and Geology (SBG) and Copernicus Hyperspectral Imaging Mission (CHIME) constellations provide global coverage with high spectral resolution and continuity. These missions offer unprecedented capabilities for detecting the subtle spectral signatures of metal stress in vegetation and soils. They build upon the success of predecessors like Hyperion and current platforms like Sentinel-2, which, with its dedicated red-edge bands, has already enabled the development of more sensitive indices (47). The vast, standardized and freely available data from these new constellations will be a catalyst for the development, validation and global adoption of next generation. Upcoming hyperspectral missions thus democratize data availability, facilitating global-scale studies and comparisons that were previously infeasible.

Towards a universal monitoring framework

The convergence of advanced remote sensing technologies, specifically spaceborne hyperspectral imaging and UAV-mounted spectrometers, enables the development of a multi-scale, integrated framework for global HM surveillance. At the macro scale, satellite-borne hyperspectral sensors (e.g., Gao fen-series, Hyperion, Zhuhai-1) provide broad spatial coverage and revisit cycles, supporting systematic detection of contamination hotspots (e.g., As and Cd across farmlands) (92). Once hotspots are flagged, airborne or UAV-based hyperspectral systems can deploy for high-resolution validation. UAV-HRS (Unmanned Aerial Hyperspectral Systems) can achieve spatial resolutions of 1-10 cm, rapid response times and significantly lower operational costs, making them highly suitable for detailed, mesoscale soil mapping (93).

Future indices should be multi-metal sensitive, enabling detection of compound contamination (e.g., simultaneous mapping of Cd, Hg and Pb); context-adaptive, dynamically adjusting to environmental variables such as soil characteristics and crop type; and actionable, offering clear interpretation to support environmental management, food safety and remediation strategies. Designing such indices will depend on a mechanistic understanding of plant-soil-metal interactions and the development of a data-sharing infrastructure that links global satellite archives with local airborne and ground-level observations.

An actionable, scalable monitoring framework would function as follows: satellite observations first continuously screen large areas to trigger alerts when abnormal spectral signatures emerge. These alerts then prompt follow-up UAV or ground-based surveys to validate and map the contamination with high precision. By offering timely, spatially explicit and accurate data, this hybrid system could inform remediation planning, guide policy responses, safeguard food safety and protect human health, thus contributing decisively to sustainability goals.

Conclusion

Heavy metal contamination in soils poses a pervasive and escalating threat to global ecosystem stability, agricultural sustainability and public health. This review provides a comprehensive synthesis of recent advances in spectral indices for monitoring soil HM contamination. It highlights that although HM lack direct spectral features, their interactions with soil constituents and impacts on plant physiology yield detectable spectral responses. The paper critically evaluates a range of indices, from traditional vegetation metrics (e.g., NDVI) to purpose-built indices (e.g., CSVI, HMSSI), emphasizing the challenges of index transferability across environments due to confounding factors such as soil moisture, texture and overlapping abiotic stresses. Looking ahead, the review underscores the transformative role of AI and machine learning in designing adaptive indices, as well as the integration of multisensor data (optical, thermal, LiDAR (Light Detection and Ranging), RADAR (Radio Detection and Ranging)) to enhance diagnostic capacity. The authors position upcoming hyperspectral missions (EnMAP, CHIME) as pivotal for validating these approaches at global scales. Overall, the review shifts the perspective from developing individual indices to constructing intelligent, scalable monitoring frameworks capable of supporting remediation, policy, food safety and sustainability objectives.

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