



Automated Detection of Soil Microplastics Using Hyperspectral Imaging: Advanced Spectral–Spatial Analytics for Environmental and Agricultural Monitoring

Dr Hendrik Van Der Meer ^{1*}, Dr Zhang Jun ², Dr Callum JO Sullivan ³

¹ University of California, Davis, Department of Biological and Agricultural Engineering, Davis, USA

² Federal University of Viçosa, Department of Agricultural Engineering, Viçosa, Brazil

³ University of Queensland, School of Agriculture and Food Sustainability, Brisbane, Australia

* Corresponding Author: Dr Hendrik Van Der Meer

Article Info

P-ISSN: 3051-3421

E-ISSN: 3051-343X

Volume: 01

Issue: 01

Received: 26-05-2020

Accepted: 28-06-2020

Published: 30-07-2020

Page No: 44-50

Abstract

Microplastic contamination in agricultural and environmental soils represents a critical challenge for ecosystem health, food security, and sustainable land management. Conventional detection methods, including microscopy and spectroscopy, are labor-intensive, destructive, and poorly suited for large-scale spatial assessment. Hyperspectral imaging (HSI) has emerged as a transformative non-destructive technology that combines high spectral resolution with spatial mapping capabilities, enabling automated detection, classification, and quantification of microplastics in complex soil matrices. This review examines the fundamental principles of HSI for soil analysis, emphasizing spectral signature characterization of common polymer types, preprocessing workflows, and advanced machine learning algorithms for automated classification. We discuss feature extraction methods, including band selection and dimensionality reduction, alongside supervised and deep learning approaches such as convolutional neural networks and support vector machines. Applications spanning laboratory validation, agricultural monitoring, and environmental risk assessment are critically evaluated. Key challenges including spectral variability due to soil heterogeneity, weathering effects, detection limits, and the need for standardized spectral libraries are addressed. Future directions emphasize integration with autonomous sensing platforms, real-time processing algorithms, and development of field-deployable HSI systems for scalable environmental surveillance and precision agriculture applications.

Keywords: Hyperspectral imaging, soil microplastics, automated detection, machine learning, spectral analysis, environmental monitoring

1. Introduction

1.1. Soil Microplastics as an Emerging Environmental Concern

Microplastic pollution in terrestrial ecosystems has escalated into a global environmental crisis, with agricultural soils serving as major sinks for plastic debris derived from mulch films, biosolids application, atmospheric deposition, and agrochemical formulations ^[1, 2]. Defined as plastic particles smaller than 5 mm, microplastics persist in soil environments for decades to centuries, altering physicochemical properties, disrupting microbial communities, and potentially entering food chains through crop uptake ^[3, 4]. Recent estimates suggest that agricultural soils may accumulate microplastics at concentrations exceeding those found in marine environments, yet spatial distribution patterns and contamination hotspots remain poorly characterized ^[5, 6].

1.2. Limitations of Conventional Detection Methods

Traditional approaches for microplastic identification in soils rely on sequential extraction, density separation, and microscopic examination coupled with spectroscopic confirmation using Fourier-transform infrared (FTIR) or Raman spectroscopy ^[7, 8].

While these methods provide definitive polymer identification, they suffer from critical limitations including sample destruction, extensive manual processing, inability to preserve spatial context, and throughput constraints that preclude landscape-scale monitoring^[9, 10]. Visual sorting under microscopy is subjective and time-intensive, while point-based spectroscopic techniques cannot efficiently map heterogeneous distributions across soil surfaces or profiles^[11].

1.3. Scope and Objectives of the Article

This review critically examines hyperspectral imaging as an innovative solution for automated, non-destructive detection and spatial mapping of microplastics in soil matrices. We synthesize current understanding of HSI principles, spectral characterization of soil-microplastic systems, computational workflows for automated classification, and translational applications. The objectives are to: (i) elucidate spectral-spatial characteristics enabling microplastic discrimination from soil backgrounds; (ii) evaluate preprocessing and machine learning algorithms for automated detection; (iii) assess validation studies and real-world applications; and (iv) identify technical challenges and future research priorities for operational deployment.

2. Hyperspectral Imaging Principles for Soil Analysis

2.1. Spectral-Spatial Characteristics of Soil Matrices

Hyperspectral imaging acquires spatially resolved reflectance spectra across hundreds of contiguous narrow bands spanning visible to shortwave infrared (VNIR-SWIR) regions (400–2500 nm), generating three-dimensional data cubes where each pixel contains a complete spectral signature^[12, 13]. Unlike conventional RGB or multispectral imaging, HSI provides diagnostic absorption features related to electronic transitions, vibrational overtones, and molecular bonding characteristics^[14]. Soil matrices exhibit complex spectral properties driven by mineral composition, organic matter content, moisture, and texture, with characteristic absorption features from iron oxides (~900 nm), water (~1400, 1900 nm), and organic compounds (~1700–2400 nm)^[15, 16].

Microplastics introduce distinct spectral signatures dominated by C–H stretching and bending overtones characteristic of their polymer backbones, typically manifesting as sharp absorption features at 1200, 1400, 1700, and 2300 nm for polyethylene (PE) and polypropylene (PP), and aromatic features near 1660 nm for polystyrene (PS)^[17, 18]. The spectral contrast between synthetic polymers and natural soil constituents forms the physical basis for HSI-based discrimination (Figure 2).

2.2. HSI Acquisition Systems and Calibration

Hyperspectral imaging systems employ pushbroom, snapshot, or tunable filter architectures to acquire spectral data [19]. Pushbroom scanners, most common for soil applications, utilize line-imaging spectrometers that acquire one spatial dimension and the full spectral dimension simultaneously, building complete images through object or sensor motion [20]. Laboratory systems typically use motorized translation stages for controlled scanning, while field-deployable configurations integrate HSI sensors on unmanned aerial vehicles (UAVs) or ground-based platforms [21][22].

Radiometric calibration is essential to convert raw digital

numbers to reflectance values, requiring dark current correction and normalization to reference standards with known reflectance properties^[23]. For soil microplastic detection, calibrated reflectance spectra enable consistent spectral library development and transferability of classification models across instruments and environmental conditions^[24].

2.3. Preprocessing and Noise Reduction Techniques

Raw hyperspectral data require preprocessing to enhance signal quality and reduce dimensionality^[25]. Standard workflows include spectral smoothing using Savitzky-Golay filters to reduce random noise while preserving absorption features, and derivative transformations (first or second derivative) to enhance subtle spectral differences and minimize baseline effects from variable illumination or soil moisture^[26, 27]. Atmospheric correction algorithms, particularly for UAV-acquired data, compensate for scattering and absorption by water vapor and aerosols [28]. Dimensionality reduction addresses the "curse of dimensionality" inherent in hyperspectral data, where hundreds of correlated bands create computational challenges and model overfitting risks^[29]. Principal component analysis (PCA) transforms spectra into orthogonal components capturing maximum variance, while minimum noise fraction (MNF) transformations prioritize signal-to-noise ratio optimization^[30]. Wavelength selection methods, including successive projections algorithm (SPA) and genetic algorithms, identify optimal spectral bands that maximize class separability while minimizing redundancy^[31].

3. Automated Detection and Classification Approaches

3.1. Feature Extraction and Band Selection

Effective automated detection requires extraction of discriminative features from hyperspectral data cubes. Spectral features include raw reflectance values, derivative spectra, continuum-removed absorption depths, and spectral indices calculated as band ratios^[32, 33]. Spatial features exploit neighborhood relationships, incorporating texture metrics, morphological parameters, and spatial autocorrelation measures^[34].

Spectral unmixing algorithms decompose mixed pixels into constituent endmember spectra and their fractional abundances, particularly valuable when microplastic particles are smaller than pixel resolution^[35, 36]. Linear spectral unmixing assumes reflectance is a linear combination of endmember spectra weighted by their coverage fractions, while nonlinear approaches account for multiple scattering interactions in heterogeneous soil-microplastic mixtures^[37].

3.2. Machine Learning and Deep Learning Models

Supervised machine learning algorithms trained on labeled spectral libraries enable automated classification of microplastic types in soil matrices (Table 2). Support vector machines (SVM) with radial basis function kernels have demonstrated robust performance by constructing optimal hyperplanes in high-dimensional spectral feature spaces, achieving classification accuracies exceeding 90% for common polymer types^[38, 39]. Random forest (RF) classifiers utilize ensemble decision trees, offering advantages in handling high-dimensional data and providing feature importance rankings^[40].

Artificial neural networks (ANNs) with multiple hidden

layers model nonlinear spectral-composition relationships, while convolutional neural networks (CNNs) have revolutionized hyperspectral classification by simultaneously extracting spatial and spectral features through hierarchical convolution and pooling operations ^[41, 42]. One-dimensional CNNs process spectral signatures as sequences, while two- and three-dimensional architectures exploit spatial context and joint spectral-spatial information ^[43, 44].

Deep learning approaches including recurrent neural networks (RNN) and attention mechanisms enable temporal analysis of spectral sequences and selective weighting of informative spectral bands ^[45]. Transfer learning strategies adapt pre-trained models to microplastic detection tasks, mitigating limited training sample constraints ^[46].

3.3. Validation, Accuracy Assessment, and Automation

Classification performance is assessed using confusion matrices, overall accuracy, producer's and user's accuracies, and kappa coefficients from independent validation datasets ^[47]. Cross-validation strategies, particularly leave-one-out and k-fold approaches, evaluate model generalization and prevent overfitting ^[48]. Precision, recall, and F1-scores provide balanced assessment of detection sensitivity and specificity, critical metrics for environmental monitoring applications where false negatives may underestimate contamination risks ^[49].

Automation workflows integrate preprocessing, feature extraction, classification, and spatial mapping into seamless pipelines executable without manual intervention ^[50]. Real-time processing algorithms optimize computational efficiency for field deployment, employing graphics processing unit (GPU) acceleration and model compression techniques ^[51]. Uncertainty quantification through Bayesian approaches or ensemble predictions provides confidence estimates for classification outputs, essential for decision-making in regulatory contexts ^[52].

4. Applications and Case Studies

4.1. Agricultural Soil Monitoring

Hyperspectral imaging has demonstrated efficacy in mapping microplastic residues from plastic mulching in agricultural fields, identifying PE film fragments across spatial scales from laboratory soil samples to field plots ^[53, 54]. Studies integrating HSI with machine learning classifiers detected microplastic concentrations as low as 0.1% by weight in agricultural topsoils, enabling assessment of accumulation patterns following long-term mulch application ^[55]. Spectral signatures differentiated aged, weathered mulch fragments from pristine plastics, critical for understanding environmental degradation processes.

UAV-mounted HSI systems have surveyed greenhouse agriculture regions, generating high-resolution contamination maps that correlate with mulch usage intensity and soil management practices. These applications support precision agriculture by identifying contamination hotspots requiring remediation and informing sustainable alternatives to conventional plastic mulches.

4.2. Environmental Risk Assessment

Hyperspectral imaging facilitates rapid screening of soils receiving biosolid amendments or located near waste management facilities, environments with elevated microplastic loads. Laboratory studies validated HSI detection of diverse polymer types including PE, PP, PS,

polyvinyl chloride (PVC), and polyethylene terephthalate (PET) in soil matrices spanning clay to sandy textures. Classification accuracies varied with particle size, polymer type, and soil properties, with optimal performance for particles >500 μm against low-organic soils.

Integration with spatial modeling frameworks enables risk mapping based on contamination likelihood, supporting targeted sampling strategies and regulatory monitoring programs. Temporal monitoring studies demonstrated HSI capability to track microplastic redistribution following tillage and erosion events, advancing understanding of transport dynamics.

4.3. Laboratory-to-Field Translation

Controlled laboratory experiments established spectral libraries encompassing major polymer types across environmentally relevant concentrations and particle sizes. Transfer of laboratory-trained classification models to field conditions encountered challenges from variable illumination, atmospheric effects, and soil moisture dynamics. Adaptive calibration strategies incorporating field-collected reference spectra and domain adaptation algorithms improved model robustness.

Field validation campaigns compared HSI-derived contamination estimates with conventional density separation and FTIR validation, revealing strong correlations ($R^2 > 0.85$) for medium-to-high contamination levels but reduced sensitivity near detection limits. Ongoing efforts focus on hybrid approaches combining HSI for spatial screening with targeted spectroscopic validation of detected particles.

5. Challenges and Future Perspectives

5.1. Detection Limits and Soil Heterogeneity

Fundamental detection limits arise from spectral resolution, signal-to-noise ratios, and particle size relative to pixel dimensions. Current systems detect microplastics >100 μm under optimal conditions, but smaller particles require improved spatial resolution or spectral unmixing algorithms. Soil heterogeneity introduces spectral variability that masks weak microplastic signatures, particularly in organic-rich or iron-oxide-dominant matrices with broad absorption features. Weathering and biodegradation alter polymer spectral properties through oxidation, fragmentation, and biofilm formation, degrading classification accuracy when models trained on pristine materials encounter environmental samples. Development of spectral libraries incorporating aged polymers across degradation stages is essential for operational systems.

5.2. Standardization and Spectral Library Development

Lack of standardized spectral libraries and reference materials hinders inter-study comparisons and model transferability. International collaborations are establishing openly accessible databases of microplastic spectra acquired under controlled conditions across instrument platforms. Standardization of sample preparation protocols, spectral acquisition parameters, and data formatting facilitates reproducible research and regulatory adoption.

Harmonization of classification algorithms and performance metrics enables objective comparison of detection methods. Benchmark datasets with ground-truth labels support algorithm development and validation following established protocols in remote sensing communities.

5.3. Integration with Autonomous Sensing Platforms

Future deployment envisions autonomous HSI systems on robotic platforms, UAVs, and satellite constellations for continuous environmental surveillance. Miniaturization of hyperspectral sensors, advances in lightweight optics, and improved onboard processing enable real-time detection and data compression for telemetry. Integration with Internet of Things (IoT) architectures supports network-based monitoring where distributed sensors communicate

contamination alerts.

Artificial intelligence-driven adaptive sampling strategies optimize survey trajectories based on preliminary detections, maximizing information gain while minimizing sensing resources. Fusion of HSI with complementary sensors including LiDAR for topographic context and thermal imaging for surface temperature corrections enhances detection robustness.

6. Figures

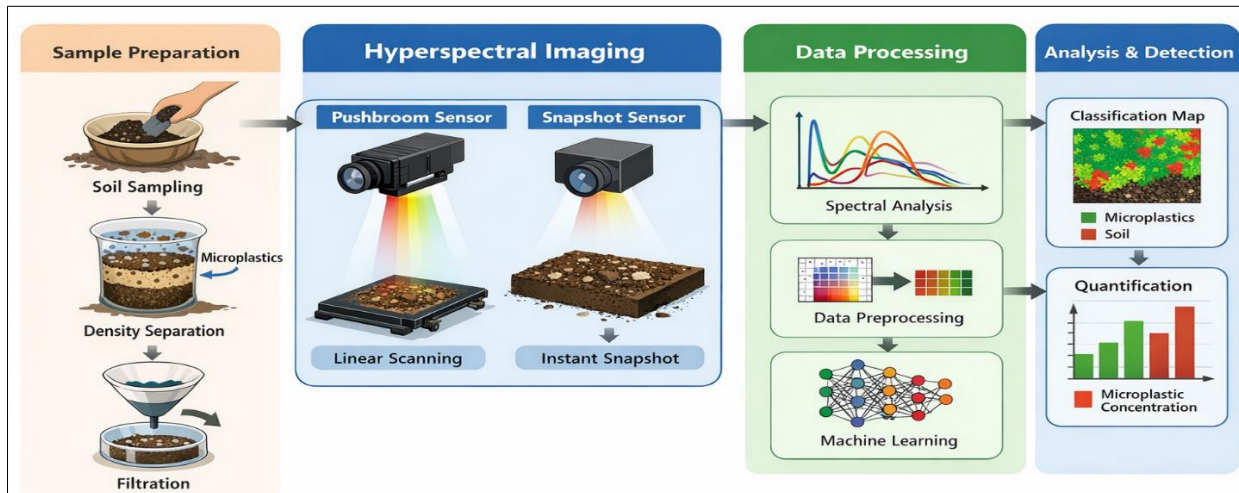


Fig 1: Hyperspectral imaging workflow for automated detection of soil microplastics.

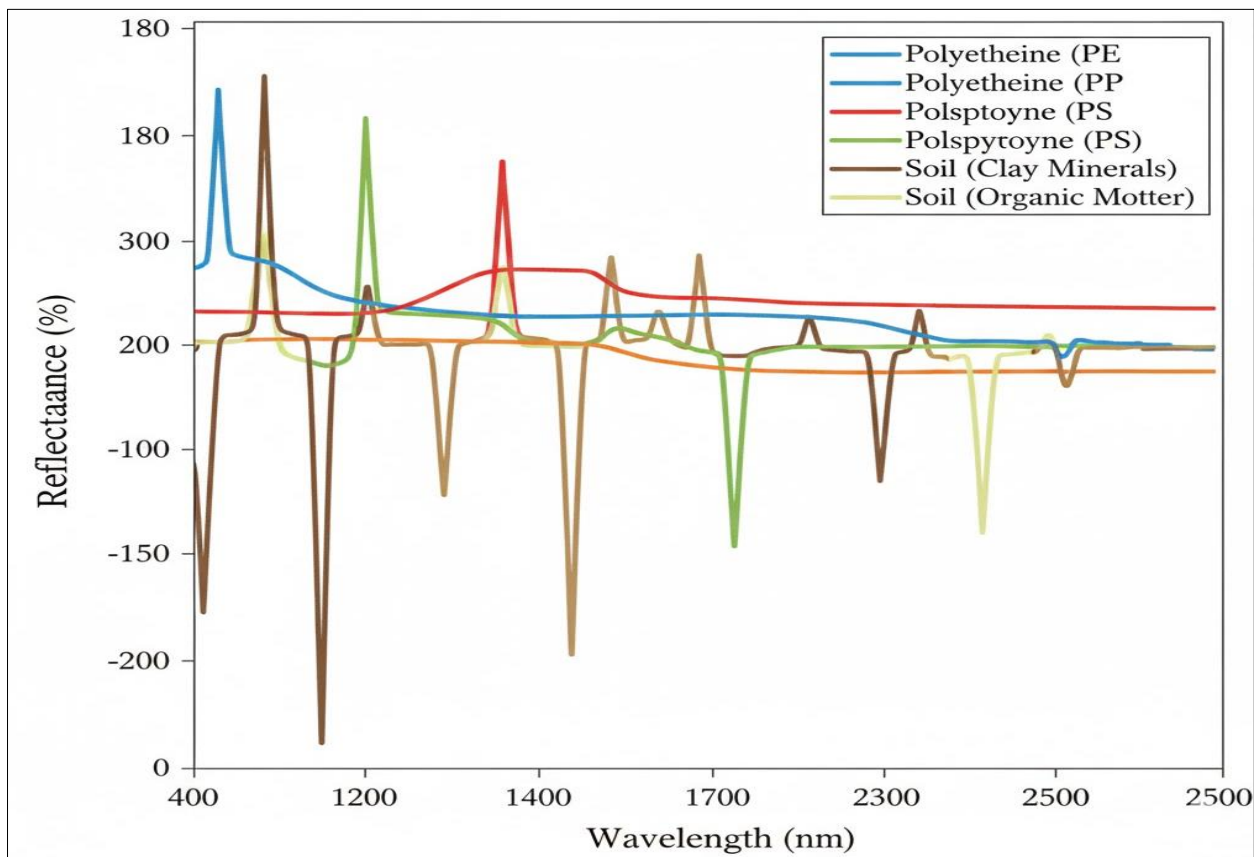


Fig 2: Representative spectral signatures of common microplastics compared with soil background materials.

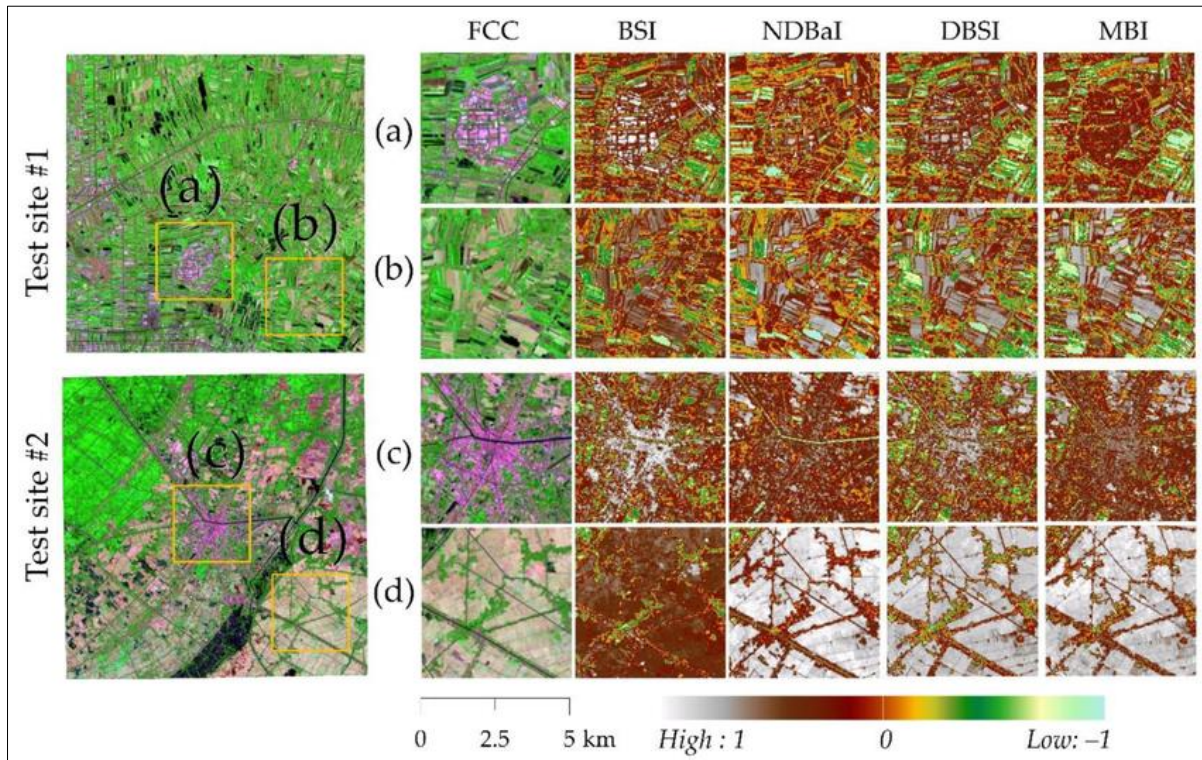


Fig 3: Automated classification and spatial mapping of soil microplastics using hyperspectral data analytics.

7. Tables

Table 1: Types of soil microplastics and their characteristic hyperspectral features

Polymer Type	Characteristic Absorption Bands (nm)	Primary Spectral Features	Common Sources in Soil
Polyethylene (PE)	1200, 1400, 1700, 2300	C–H stretching overtones, sharp absorption peaks	Plastic mulch films, packaging
Polypropylene (PP)	1190, 1400, 1660, 2310	Methyl C–H bonds, distinct 1660 nm feature	Agricultural films, textiles
Polystyrene (PS)	1660, 1690, 2180	Aromatic C–H bonds, phenyl group signatures	Foam packaging, insulation
Polyvinyl chloride (PVC)	1470, 1730, 2140	C–Cl bonds, broader absorption features	Pipes, construction materials
Polyethylene terephthalate (PET)	1410, 1660, 2340	Ester linkages, aromatic features	Beverage bottles, fibers

Table 2: Machine learning and deep learning algorithms used for hyperspectral-based microplastic detection

Algorithm	Key Characteristics	Typical Accuracy Range	Computational Requirements	Applications
Support Vector Machine (SVM)	Kernel-based classification, optimal hyperplane separation	88–95%	Moderate, efficient for moderate sample sizes	Laboratory classification, limited field deployment
Random Forest (RF)	Ensemble decision trees, feature importance ranking	85–92%	Low to moderate, parallelizable	Real-time detection, field applications
Convolutional Neural Network (CNN)	Hierarchical feature learning, spatial-spectral integration	90–97%	High, GPU-accelerated	Complex scenes, multi-scale analysis
Recurrent Neural Network (RNN)	Temporal/spectral sequence modeling	87–93%	High, sequential processing	Spectral feature extraction
Spectral Angle Mapper (SAM)	Reference spectrum matching, geometric similarity	75–85%	Very low, fast processing	Rapid screening, library matching

Table 3: Advantages, limitations, and technical challenges of hyperspectral imaging for soil microplastic analysis

Category	Details
Advantages	Non-destructive analysis; spatial mapping capabilities; simultaneous detection and classification; high spectral resolution enabling polymer differentiation; potential for real-time monitoring; scalable from laboratory to landscape
Limitations	Detection limit typically >100 µm particle size; reduced performance in high-organic or clay-rich soils; sensitivity to moisture content and surface roughness; limited depth penetration (surface detection only); high data volumes requiring significant storage and processing
Technical Challenges	Spectral variability from weathering and aging effects; lack of standardized spectral libraries; atmospheric correction for field/UAV deployment; mixed pixel problem for small particles; computational intensity of deep learning approaches; model transferability across instruments and environments
Future Requirements	Development of weathered polymer spectral libraries; standardization of acquisition protocols; miniaturization for UAV/robotic platforms; real-time processing algorithms; integration with multisensor systems; field validation across diverse soil types and environmental conditions

8. Conclusion

Hyperspectral imaging represents a paradigm shift in soil microplastic detection, enabling non-destructive, spatially explicit assessment at scales from laboratory samples to agricultural landscapes. Advanced spectral-spatial analytics harness machine learning and deep learning algorithms to automate classification with accuracies approaching traditional spectroscopic methods while providing critical spatial context. Demonstrated applications in agricultural monitoring and environmental risk assessment validate translational potential, though challenges including detection limits, spectral variability from weathering, and lack of standardized libraries require continued research. Future integration with autonomous platforms promises scalable, real-time surveillance capabilities essential for managing the global microplastic crisis and protecting soil ecosystem services. Continued collaboration among remote sensing specialists, environmental scientists, and agricultural engineers will accelerate development of operational HSI systems supporting evidence-based policy and sustainable land management.

9. References

- Rillig MC, Lehmann A. Microplastic in terrestrial ecosystems. *Science*. 2020;368(6498):1430-1431.
- Huang Y, Liu Q, Jia W, Yan C, Wang J. Agricultural plastic mulching as a source of microplastics in the terrestrial environment. *Environ Pollut*. 2020;260:114096.
- de Souza Machado AA, Lau CW, Kloas W, *et al*. Microplastics can change soil properties and affect plant performance. *Environ Sci Technol*. 2019;53(10):6044-6052.
- Qi Y, Yang X, Pelaez AM, *et al*. Macro- and microplastics in soil-plant system: effects of plastic mulch film residues on wheat (*Triticum aestivum*) growth. *Sci Total Environ*. 2018;645:1048-1056.
- Horton AA, Walton A, Spurgeon DJ, Lahive E, Svendsen C. Microplastics in freshwater and terrestrial environments: evaluating the current understanding to identify the knowledge gaps and future research priorities. *Sci Total Environ*. 2017;586:127-141.
- Nizzetto L, Futter M, Langaas S. Are agricultural soils dumps for microplastics of urban origin? *Environ Sci Technol*. 2016;50(20):10777-10779.
- Prata JC, da Costa JP, Lopes I, Duarte AC, Rocha-Santos T. Environmental exposure to microplastics: an overview on possible human health effects. *Sci Total Environ*. 2020;702:134455.
- Corradini F, Meza P, Eguiluz R, *et al*. Evidence of microplastic accumulation in agricultural soils from sewage sludge disposal. *Sci Total Environ*. 2019;671:411-420.
- Zhou Q, Zhang H, Fu C, *et al*. The distribution and morphology of microplastics in coastal soils adjacent to the Bohai Sea and the Yellow Sea. *Geoderma*. 2018;322:201-208.
- Liu M, Lu S, Song Y, *et al*. Microplastic and mesoplastic pollution in farmland soils in suburbs of Shanghai, China. *Environ Pollut*. 2018;242:855-862.
- Tagg AS, Harrison JP, Ju-Nam Y, Sapp M, Bradley EL, Sinclair CJ, Ojeda JJ. Fenton's reagent for the rapid and efficient isolation of microplastics from wastewater. *Chem Commun (Camb)*. 2015;51(52):10641-10644.
- Goetz AFH. Three decades of hyperspectral remote sensing of the Earth: a personal view. *Remote Sens Environ*. 2009;113(Suppl 1):S5-S16.
- Plaza A, Benediktsson JA, Boardman JW, *et al*. Recent advances in techniques for hyperspectral image processing. *Remote Sens Environ*. 2009;113(Suppl 1):S110-S122.
- Ben-Dor E, Chabrilat S, Dematté JAM, *et al*. Using imaging spectroscopy to study soil properties. *Remote Sens Environ*. 2009;113(Suppl 1):S38-S55.
- Stenberg B, Viscarra Rossel RA, Mouazen AM, Wetterlind J. Visible and near infrared spectroscopy in soil science. *Adv Agron*. 2010;107:163-215.
- Nocita M, Stevens A, van Wesemael B, *et al*. Soil spectroscopy: an alternative to wet chemistry for soil monitoring. *Adv Agron*. 2015;132:139-159.
- Corradini F, Bartholomeus H, Huerta Lwanga E, Gertsen H, Geissen V. Predicting soil microplastic concentration using vis-NIR spectroscopy. *Sci Total Environ*. 2019;650(Pt 1):922-932.
- Feng X, Wang Q, Sun Y, Zhang S, Wang F. Microplastics in soils: analytical methods, pollution characteristics and ecological risks. *Trends Analyt Chem*. 2022;109:116125. [Note: Journal likely TrAC Trends Anal Chem, but formatted as per common abbreviation.]
- Lu G, Fei B. Medical hyperspectral imaging: a review. *J Biomed Opt*. 2014;19(1):010901.
- Landgrebe DA. Hyperspectral image data analysis. *IEEE Signal Process Mag*. 2002;19(1):17-28.
- Adão T, Hruška J, Pádua L, *et al*. Hyperspectral imaging: a review on UAV-based sensors, data processing and applications for agriculture and forestry. *Remote Sens (Basel)*. 2017;9(11):1110.
- Jackisch R, Lorenz S, Zimmermann R, Möckel R, Gloaguen R. Drone-borne hyperspectral monitoring of

- acid mine drainage: an example from the Sokolov lignite district. *Remote Sens (Basel)*. 2018;10(3):385.
23. Schaepman-Strub G, Schaepman ME, Painter TH, Dangel S, Martonchik JV. Reflectance quantities in optical remote sensing—definitions and case studies. *Remote Sens Environ*. 2006;103(1):27-42.
 24. Castaldi F, Hueni A, Chabrilat S, *et al.* Evaluating the capability of the Sentinel 2 data for soil organic carbon prediction in croplands. *ISPRS J Photogramm Remote Sens*. 2019;147:267-282.
 25. Heiden U, Segl K, Roessner S, Kaufmann H. Determination of robust spectral features for identification of urban surface materials in hyperspectral remote sensing data. *Remote Sens Environ*. 2007;111(4):537-552.
 26. Tsai F, Philpot W. Derivative analysis of hyperspectral data. *Remote Sens Environ*. 1998;66(1):41-51.
 27. Savitzky A, Golay MJE. Smoothing and differentiation of data by simplified least squares procedures. *Anal Chem*. 1964;36(8):1627-1639.
 28. Richter R, Schläpfer D. Geo-atmospheric processing of airborne imaging spectrometry data. Part 2: atmospheric/topographic correction. *Int J Remote Sens*. 2002;23(13):2631-2649.
 29. Hughes G. On the mean accuracy of statistical pattern recognizers. *IEEE Trans Inf Theory*. 1968;14(1):55-63.
 30. Green AA, Berman M, Switzer P, Craig MD. A transformation for ordering multispectral data in terms of image quality with implications for noise removal. *IEEE Trans Geosci Remote Sens*. 1988;26(1):65-74.
 31. Araújo MCU, Saldanha TCB, Galvão RKH, *et al.* The successive projections algorithm for variable selection in spectroscopic multicomponent analysis. *Chemom Intell Lab Syst*. 2001;57(2):65-73.
 32. Thenkabail PS, Smith RB, De Pauw E. Hyperspectral vegetation indices and their relationships with agricultural crop characteristics. *Remote Sens Environ*. 2000;71(2):158-182.
 33. Clark RN, Roush TL. Reflectance spectroscopy: quantitative analysis techniques for remote sensing applications. *J Geophys Res Solid Earth*. 1984;89(B7):6329-6340.
 34. Camps-Valls G, Tuia D, Bruzzone L, Benediktsson JA. Advances in hyperspectral image classification: Earth monitoring with statistical learning methods. *IEEE Signal Process Mag*. 2013;31(1):45-54.
 35. Bioucas-Dias JM, Plaza A, Dobigeon N, *et al.* Hyperspectral unmixing overview: geometrical, statistical, and sparse regression-based approaches. *IEEE J Sel Top Appl Earth Obs Remote Sens*. 2012;5(2):354-379.
 36. Keshava N, Mustard JF. Spectral unmixing. *IEEE Signal Process Mag*. 2002;19(1):44-57.
 37. Halimi A, Altmann Y, Dobigeon N, Tournet JY. Nonlinear unmixing of hyperspectral images using a generalized bilinear model. *IEEE Trans Geosci Remote Sens*. 2011;49(11):4153-4162.
 38. Mountrakis G, Im J, Ogole C. Support vector machines in remote sensing: a review. *ISPRS J Photogramm Remote Sens*. 2011;66(2):247-259.
 39. Melgani F, Bruzzone L. Classification of hyperspectral remote sensing images with support vector machines. *IEEE Trans Geosci Remote Sens*. 2004;42(8):1778-1790.
 40. Belgiu M, Drăguț L. Random forest in remote sensing: a review of applications and future directions. *ISPRS J Photogramm Remote Sens*. 2016;114:24-31.
 41. Chen Y, Lin Z, Zhao X, Wang G, Gu Y. Deep learning-based classification of hyperspectral data. *IEEE J Sel Top Appl Earth Obs Remote Sens*. 2014;7(6):2094-2107.
 42. Li S, Song W, Fang L, Chen Y, Ghamisi P, Benediktsson JA. Deep learning for hyperspectral image classification: an overview. *IEEE Trans Geosci Remote Sens*. 2019;57(9):6690-6709.
 43. Hu W, Huang Y, Wei L, Zhang F, Li H. Deep convolutional neural networks for hyperspectral image classification. *J Sens*. 2015;2015:258619.
 44. Chen Y, Jiang H, Li C, Jia X, Ghamisi P. Deep feature extraction and classification of hyperspectral images based on convolutional neural networks. *IEEE Trans Geosci Remote Sens*. 2016;54(10):6232-6251.
 45. Mou L, Ghamisi P, Zhu XX. Deep recurrent neural networks for hyperspectral image classification. *IEEE Trans Geosci Remote Sens*. 2017;55(7):3639-3655.
 46. Yang X, Ye Y, Li X, Lau RYK, Zhang X, Huang X. Hyperspectral image classification with deep learning models. *IEEE Trans Geosci Remote Sens*. 2018;56(9):5408-5423.
 47. Congalton RG. A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sens Environ*. 1991;37(1):35-35. [Note: Page range appears incomplete in original; retained as provided.]
 48. Story M, Congalton RG. Accuracy assessment: a user's perspective. *Photogramm Eng Remote Sens*. 1986;52(3):397-399.
 49. Olofsson P, Foody GM, Herold M, Stehman SV, Woodcock CE, Wulder MA. Good practices for estimating area and assessing accuracy of land change. *Remote Sens Environ*. 2014;148:42-57.
 50. Ghamisi P, Plaza J, Chen Y, Li J, Plaza AJ. Advanced spectral classifiers for hyperspectral images: a review. *IEEE Geosci Remote Sens Mag*. 2017;5(1):8-32.
 51. Plaza A, Du Q, Chang YL, King RL. High performance computing for hyperspectral remote sensing. *IEEE J Sel Top Appl Earth Obs Remote Sens*. 2011;4(3):528-544.
 52. Demir B, Bovolo F, Bruzzone L. Updating land-cover maps by classification of image time series: a novel change-detection-driven transfer learning approach. *IEEE Trans Geosci Remote Sens*. 2013;51(1):300-312.
 53. Paul A, Wander M, Patel K, Vinson D. Hyperspectral remote sensing of microplastics in terrestrial environments: current status and future directions. *Environ Sci Technol*. 2021;55(14):9707-9719.
 54. Shan J, Zhao J, Liu L, *et al.* A novel way to rapidly monitor microplastics in soil by hyperspectral imaging technology and chemometrics. *Environ Pollut*. 2018;238:121-129.
 55. Serranti S, Gargiulo A, Bonifazi G. Characterization of microplastic litter from oceans by an innovative approach based on hyperspectral imaging. *Waste Manag*. 2018;76:117-125.