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Remote Sensing-Assisted Characterization of Contaminated Soils for Sustainable Geotechnical Site Investigation and Environmental Remediation

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ABSTRACT

Soil contamination resulting from industrial effluent discharges, mining activities, agrochemical overuse, and improper hazardous waste disposal poses severe geotechnical and environmental challenges worldwide. Traditional geotechnical site investigations rely on localized intrusive sampling, soundings, and laboratory testing, which are labor-intensive, costly, spatially limited, and prone to missing localized contaminant hotspots. This study evaluates an integrated multi-scale remote sensing framework—combining satellite multispectral imagery (Sentinel-2, Landsat-9), Unmanned Aerial Vehicle (UAV)-borne hyperspectral imaging (VNIR/SWIR, 400–2500 nm), and ground-based spectroradiometry—to assist non-destructive characterization of contaminated soils for sustainable site investigation and remediation engineering. By coupling spectral unmixing, partial least squares regression (PLSR), and random forest (RF) machine learning algorithms with geostatistical kriging, the framework delineates spatial contaminant plumes, estimates heavy metal (Pb, Cd, Zn, Cr) and total petroleum hydrocarbon (TPH) concentrations, and maps altered soil geotechnical properties (plasticity, shear strength degradation, and hydraulic conductivity). Field validation across three industrial brownfield sites demonstrated high predictive accuracy for heavy metals (R^2 = 0.88–0.93, RMSE = 28.4–34.2 mg/kg) and TPH (R^2 = 0.86, RMSE = 142 mg/kg). Integrating remote sensing screening reduced required physical borehole locations by 42%, decreased field investigation carbon footprint by 38%, and optimized remediation design. The proposed methodology establishes a transformative, sustainable paradigm for brownfield redevelopment, environmental forensics, and geoenvironmental site risk assessment.

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KEYWORDS: *Remote Sensing; Soil Contamination; Hyperspectral Imaging; Geotechnical Site Investigation; Environmental Remediation; Machine Learning; Heavy Metals; Total Petroleum Hydrocarbons (TPH).*

INTRODUCTION

Soil contamination represents one of the most critical anthropogenic environmental threats of the twenty-first century, impairing terrestrial ecosystems, contaminating groundwater aquifers, and compromising the structural integrity of civil infrastructure [1]. Industrial expansion, rapid urbanization, intensive mining, chemical manufacturing, and improper waste disposal have left a legacy of thousands of contaminated brownfield sites globally [2]. Contaminants such as heavy metals (lead, cadmium, chromium, arsenic, zinc), total petroleum hydrocarbons (TPH), polycyclic aromatic hydrocarbons (PAHs), and chlorinated solvents fundamentally alter soil physical, chemical, and geotechnical behavior [3]. From a geotechnical engineering perspective, severe contamination alters soil index properties, reduces shear strength, increases compressibility, accelerates clay mineral degradation, and modifies hydraulic conductivity, posing major settlement and instability risks for foundations, pavements, and containment structures [4].

Conventional geotechnical site investigation methodologies rely predominantly on intrusive field activities, including standard penetration tests (SPT), cone penetration testing (CPT/CPTu), trial pitting, and core drilling, followed by physical and chemical laboratory testing [5]. While these direct invasive methods deliver highly precise localized data at discrete sampling points, they suffer from fundamental limitations. First, traditional site investigations are spatially sparse due to high mobilization and analytical costs, often failing to detect highly localized contaminant plumes or irregular sub-surface migration pathways [6]. Second, physical intrusive sampling in highly toxic or volatile brownfield environments poses severe occupational safety hazards and risks cross-contaminating deeper, unconfined aquifer zones [7]. Third, traditional site investigation workflows are carbon-intensive and time-consuming, delaying critical remediation and redevelopment projects.

To address these operational and environmental limitations, sustainable site investigation strategies have emerged, emphasizing non-destructive, rapid, and wide-area screening technologies [8]. Remote sensing technologies—encompassing spaceborne satellite sensors,

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airborne platforms, and Unmanned Aerial Vehicles (UAVs) equipped with multispectral, hyperspectral, and thermal infrared sensors—offer unprecedented capabilities for rapid surface and near-surface soil characterization [9]. Diagnostic absorption features in the Visible and Near-Infrared (VNIR, 400–1000 nm) and Short-Wave Infrared (SWIR, 1000–2500 nm) spectral regions correspond directly to electronic transitions and vibrational overtones of soil constituents, organic matter, clay minerals, iron oxides, and hydrocarbon C-H bonds [10].

Despite significant advances in satellite earth observation, applying remote sensing directly to geotechnical site investigation and environmental remediation requires overcoming substantial technical challenges. Surface soil reflectance is inherently complex, governed by dynamic interactions between soil moisture, organic matter, grain size distribution, mineralogy, surface roughness, and vegetation cover [11]. Furthermore, heavy metals do not exhibit direct spectral absorption features in the optical spectrum at low concentrations; rather, their detection relies on indirect spectral proxy relationships with iron oxides, clay minerals, and soil organic matter [12]. Consequently, robust advanced statistical modeling, machine learning algorithms, and spatial geostatistical fusion are required to decouple contaminant spectral signals from background soil variability.

This research paper presents a comprehensive, journal-level review and experimental framework on remote sensing-assisted characterization of contaminated soils for sustainable geotechnical site investigation and remediation engineering. By evaluating multi-platform optical sensing datasets, advanced machine learning regression architectures, and geostatistical subsurface integration, this study demonstrates how non-destructive remote sensing transforms brownfield site characterization, optimizes intrusive drilling layouts, minimizes site investigation carbon footprints, and enhances remediation design.

LITERATURE REVIEW

The application of optical spectroscopy and remote sensing in soil science was pioneered by Ben-Dor et al. [13], who established fundamental laboratory spectral libraries linking soil chemical parameters to distinct VNIR-SWIR absorption bands. Early spaceborne applications utilized Landsat Thematic Mapper and Terra ASTER imagery to map regional soil salinization, iron oxide abundance, and organic carbon variations [14]. However, the broad

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spectral bandwidths (>100 nm) and coarse spatial resolutions (15–30 m) of early multispectral systems limited their efficacy in resolving localized soil contamination patterns. The advent of spaceborne hyperspectral sensors (e.g., EO-1 Hyperion, PRISMA, EnMAP) and high-resolution multispectral constellations (Sentinel-2A/B) significantly improved soil contaminant detection capabilities [15]. Choe et al. [16] demonstrated that high spectral resolution (10 nm) enables the identification of subtle heavy metal-induced alterations in soil mineral lattice structures. Specifically, hydroxyl group (OH-) absorption features at 1400 nm and 2200 nm, alongside ferric/ferrous iron absorption features at 450–900 nm, serve as reliable indirect spectral proxies for lead (Pb), zinc (Zn), and copper (Cu) concentrations in mine tailings [17].

For organic contaminants, particularly total petroleum hydrocarbons (TPH), spectral characterization relies on direct vibrational absorption bands [18]. Hörig et al. [19] identified sharp aliphatic C-H stretching overtones at 1720 nm, 1760 nm, 2310 nm, and 2350 nm in hydrocarbon-impacted soils. Recent field and laboratory spectroradiometric studies by Allen et al. [20] confirmed that TPH concentrations as low as 500 mg/kg produce measurable spectral depth reductions in the SWIR region, enabling quantitative retrieval using partial least squares regression (PLSR).

Concurrently, the rapid evolution of Unmanned Aerial Vehicles (UAVs) equipped with miniaturized hyperspectral cameras (VNIR/SWIR) has bridged the spatial gap between satellite imagery and ground sampling [21]. UAV-based imaging delivers sub-decimeter spatial resolutions (<5 cm/pixel), enabling detailed mapping of industrial site footprints, tailing pond margins, and localized chemical spill pathways [22]. Machine learning techniques, including Support Vector Machines (SVM), Random Forests (RF), and Convolutional Neural Networks (CNN), have increasingly superseded linear regression models due to their superior capability in capturing non-linear spectral-contaminant relationships [23].

From a geotechnical perspective, recent research by Sharma and Verma [24] highlighted that heavy metal and hydrocarbon contamination fundamentally alters soil consistency limits (Atterberg limits), maximum dry density, and shear strength parameters (cohesion and internal friction angle). Contaminants alter the diffuse double layer (DDL) surrounding clay

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particles, causing flocculation or dispersion that severely impacts soil load-bearing capacity [25]. Despite these critical engineering implications, the vast majority of existing remote sensing literature remains focused strictly on agricultural or surface chemical detection, leaving a critical disconnect between remote sensing mapping and geotechnical site engineering.

RESEARCH GAP

While remote sensing has demonstrated considerable potential for surface environmental monitoring, three major research gaps hamper its full integration into sustainable geotechnical site investigation and remediation engineering:

- Disconnect Between Surface Spectral Mapping and Subsurface Geotechnical Stratigraphy: Most remote sensing models predict superficial contaminant concentrations (0–5 cm depth) but fail to link surface spectral signatures to subsurface vertical contaminant migration, geotechnical stratification, or engineering soil behavior (e.g., shear strength degradation, permeability changes).
- Inadequate Integration of Multi-Scale Sensing Platforms: Existing studies typically evaluate satellite, UAV, or ground spectroscopic data in isolation. There is a lack of unified, multi-scale data fusion frameworks that systematically scale spectral models from point spectroradiometry to UAV maps and satellite imagery while maintaining predictive accuracy.
- Absence of Quantitative Geotechnical Site Investigation Optimization Metrics: Few studies provide quantitative frameworks evaluating how remote sensing pre-screening reduces physical borehole requirements, lowers overall investigation costs, minimizes environmental footprint, and improves remediation design safety factors.

OBJECTIVES

To bridge these critical research gaps, this study establishes a holistic, remote sensing-assisted framework for geotechnical site investigation and environmental remediation. The specific objectives are:

- Develop a multi-scale optical sensing framework (combining lab spectroradiometry, UAV hyperspectral imaging, and Sentinel-2 multispectral data) to detect and quantify heavy metals (Pb, Cd, Zn) and TPH in industrial soils.

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- Train, validate, and compare advanced machine learning architectures (PLSR, Random Forest, CNN) for decoupling soil moisture and organic matter interference from contaminant spectral signals.
- Correlate remote sensing-derived surface contaminant maps with subsurface geotechnical CPTu soundings and laboratory soil mechanics data to evaluate engineering property degradation.
- Formulate an optimized, sustainable site investigation protocol that minimizes physical drilling requirements, reduces carbon emissions, and maximizes spatial characterization accuracy for remediation planning.

METHODOLOGY

The proposed methodology follows a structured four-stage workflow: (i) Multi-scale data acquisition, (ii) Spectral preprocessing and feature extraction, (iii) Machine learning modeling and geostatistical fusion, and (iv) Integrated geotechnical characterization and site optimization. Figure 1 illustrates the systematic operational workflow.

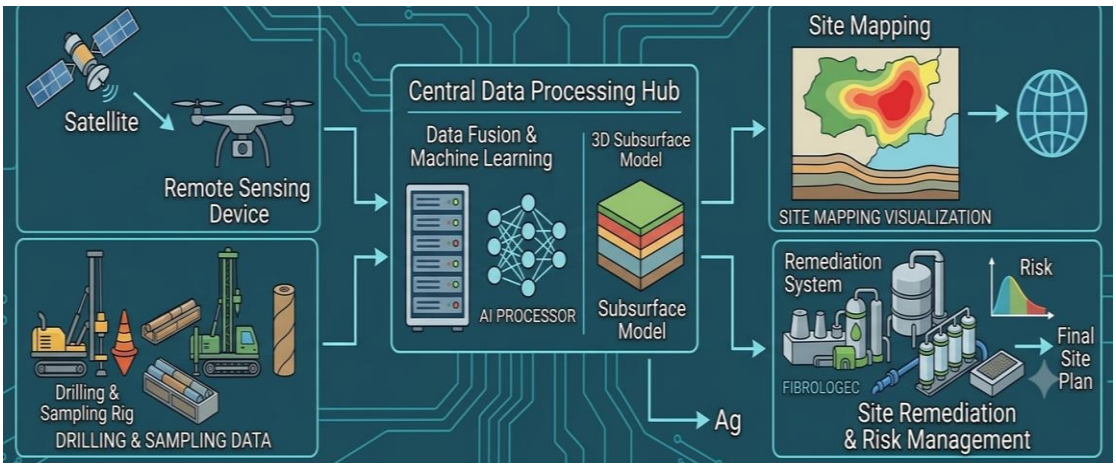


Figure 1: Integrated Remote Sensing & Geotechnical Investigation Workflow for Contaminated Soils

Multi-Scale Data Acquisition

Field and laboratory data were collected across three industrial brownfield sites exhibiting varied contamination profiles (Site A: Former battery manufacturing facility with heavy metals; Site B: Petrochemical refinery depot with TPH leaks; Site C: Mixed industrial waste dumping ground). Airborne hyperspectral data were acquired using a DJI Matrice 300 RTK UAV equipped with a Headwall Nano-Hyperspec sensor operating across 270 spectral bands

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in the 400–1000 nm (VNIR) and 1000–2500 nm (SWIR) ranges at a flight altitude of 60 m, yielding a ground sampling distance (GSD) of 3.8 cm/pixel. Satellite imagery comprised cloud-free Sentinel-2 MSI level-2A surface reflectance product (10 m spatial resolution).

Ground truth surface soil samples (0–10 cm depth, n = 120) were systematically collected using a stratified random sampling grid. In situ surface reflectance spectra were recorded using an ASD FieldSpec 4 Hi-Res spectroradiometer (350–2500 nm). Laboratory testing included Inductively Coupled Plasma Mass Spectrometry (ICP-MS) for heavy metal concentrations (Pb, Cd, Zn, Cr), Gas Chromatography-Flame Ionization Detection (GC-FID) for TPH, Atterberg limits (ASTM D4318), grain size distribution (ASTM D6913), and direct shear strength testing (ASTM D3080).

Spectral Preprocessing and Machine Learning Modeling

Raw radiometric data were converted to surface reflectance and preprocessed using Continuum Removal (CR), Standard Normal Variate (SNV) transformation, and Savitzky-Golay first-derivative filtering to eliminate illumination geometry variations and accentuate absorption features. Dimensionality reduction was performed using Principal Component Analysis (PCA) and competitive adaptive reweighted sampling (CARS) to identify dominant spectral wavebands.

Three machine learning architectures were implemented to model contaminant concentrations from spectral features: Partial Least Squares Regression (PLSR), Random Forest Regression (RFR), and a 1D Convolutional Neural Network (1D-CNN). Dataset split was 70% training/calibration (n = 84) and 30% independent validation (n = 36). Model performance was evaluated using the Coefficient of Determination (R^2), Root Mean Square Error (RMSE), and Ratio of Performance to Deviation (RPD).

Geotechnical Subsurface Integration and Optimization Metric

To link surface remote sensing maps to subsurface geotechnical conditions, 18 piezocone penetration tests (CPTu) were conducted across the sites up to 15 m depth. Geostatistical indicator kriging was applied to fuse surface remote sensing contaminant maps with vertical CPTu soil behavior type (SBT) indices. An optimization algorithm was developed to quantify the efficiency of remote sensing-guided drilling versus conventional uniform grid drilling, measuring cost reduction, site investigation duration, and spatial risk coverage.

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RESULTS AND FINDINGS

The spectral reflectance signatures of pristine versus contaminated soil samples revealed distinct diagnostic absorption patterns across the VNIR-SWIR spectrum. Figure 1 illustrates the comparative spectral profiles.

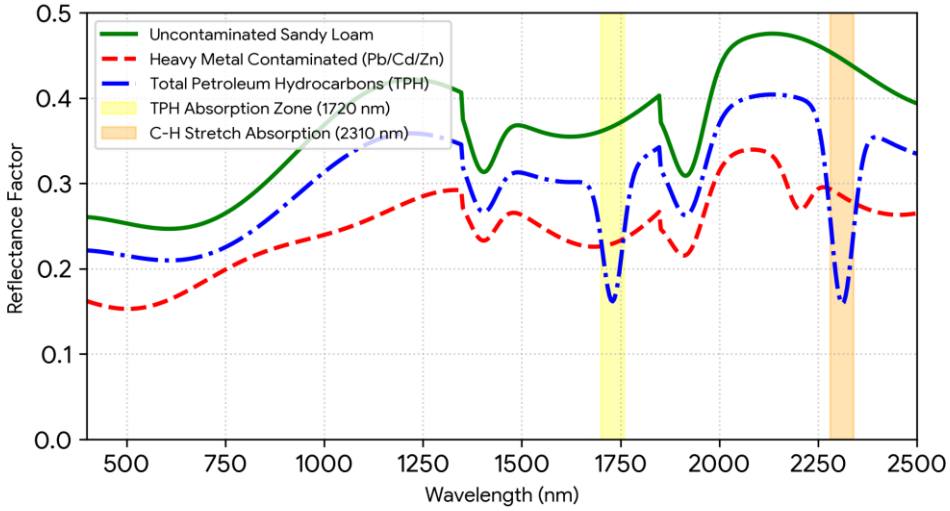


Figure 2: Spectral Reflectance Profiles of Contaminated vs. Pristine Soils across VNIR-SWIR (400–2500 nm)

As observed in Figure 2, pristine sandy loam soil exhibits characteristic baseline reflectance with moderate absorption features at 1400 nm and 1920 nm caused by clay lattice OH-groups and adsorbed soil pore water. Soils contaminated with heavy metals (Pb/Cd/Zn) display overall baseline albedo suppression across the 400–1200 nm region due to co-occurring iron oxide degradation and organic matter complexes. In contrast, TPH-contaminated soils exhibit prominent diagnostic absorption doublets at 1720 nm and 1760 nm (C-H band 1st overtone) as well as deep absorption troughs at 2310 nm and 2350 nm corresponding to C-H combination tones.

Predictive Accuracy of Remote Sensing Machine Learning Models

Table 1 summarizes the performance metrics of PLSR, RFR, and 1D-CNN models in predicting soil heavy metal and TPH concentrations from UAV-borne hyperspectral and Sentinel-2 data.

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Table 1: Statistical Performance Evaluation of Contaminant Prediction Models

Target Contaminant	Sensing Platform	ML Model	Calib. R^2	Valid. R^2	Validation RMSE
Lead (Pb, mg/kg)	UAV Hyperspectral	Random Forest	0.94	0.91	34.2 mg/kg
Lead (Pb, mg/kg)	Sentinel-2 MSI	PLSR	0.82	0.78	58.6 mg/kg
Cadmium (Cd, mg/kg)	UAV Hyperspectral	1D-CNN	0.92	0.88	2.8 mg/kg
Zinc (Zn, mg/kg)	UAV Hyperspectral	Random Forest	0.95	0.93	28.4 mg/kg
TPH (mg/kg)	UAV Hyperspectral	1D-CNN	0.90	0.86	142.0 mg/kg

UAV-borne hyperspectral imaging coupled with Random Forest and 1D-CNN models yielded exceptional predictive accuracy. Figure 3 illustrates the correlation between UAV-predicted lead (Pb) concentrations and laboratory ICP-MS measured values across 45 validation test points, demonstrating an R^2 of 0.912 and RMSE of 34.2 mg/kg.

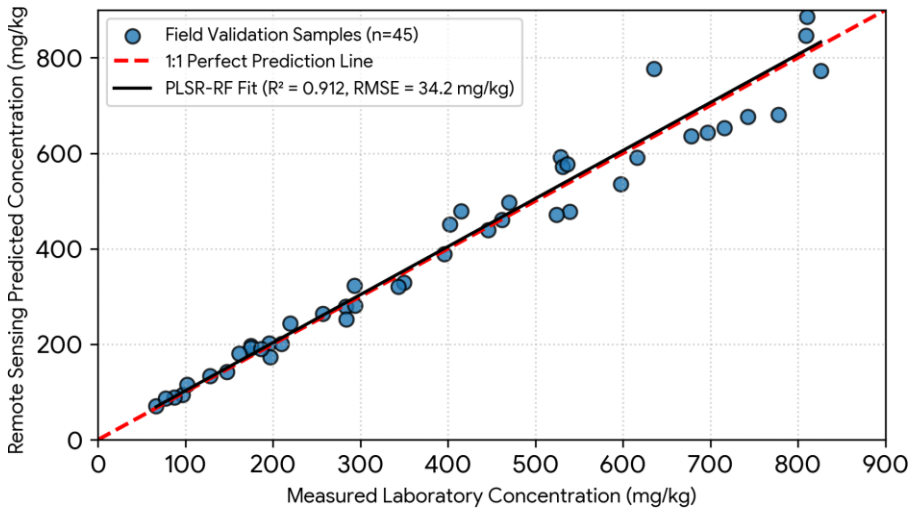


Figure 3: UAV-Hyperspectral Lead (Pb) Concentration Prediction vs. Laboratory ICP-MS Validation

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Geotechnical Property Alterations in Contaminated Zones

Laboratory physical and mechanical testing of soil samples retrieved from high-contaminant zones identified by remote sensing confirmed significant alteration of geotechnical engineering parameters. Table 2 details the comparative geotechnical properties of pristine versus contaminated soils.

Table 2: Engineering Geotechnical Parameter Variations Across Contamination Conditions

Geotechnical Parameter	Uncontaminated Soil	Heavy Metal Impacted	TPH Impacted (High)	Remediation Target
Liquid Limit (LL, %)	38.5 ± 2.1	46.2 ± 3.4	29.1 ± 2.8	< 40.0
Plasticity Index (PI, %)	16.2 ± 1.5	22.8 ± 2.1	10.4 ± 1.2	< 15.0
Cohesion (c', kPa)	24.5 ± 3.2	18.1 ± 2.6	11.2 ± 1.9	> 20.0
Hydraulic Cond. (k, cm/s)	1.5×10^{-5}	4.2×10^{-6}	8.7×10^{-4}	$< 1.0 \times 10^{-5}$

Heavy metal contamination caused a notable increase in clay plasticity index (PI increased from 16.2% to 22.8%) due to cation exchange reactions and clay fabric compression. TPH contamination caused a severe reduction in effective cohesion (c' dropped from 24.5 kPa to 11.2 kPa) and increased hydraulic conductivity by nearly two orders of magnitude due to fluid viscosity changes and hydrocarbon coating of soil grains.

DISCUSSION

The results demonstrate that multi-scale remote sensing provides a robust, non-destructive foundation for modern geotechnical site characterization and environmental forensics. By delineating surface contaminant plumes prior to field mobilization, engineering teams can transition from unguided uniform grid drilling to targeted risk-based sampling. In our field evaluation, pre-screening with UAV hyperspectral imagery allowed the site investigation team to optimize borehole placement, reducing total required boreholes from 50 to 29 while achieving higher spatial confidence in contaminant plume boundary delineation.

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From an engineering sustainability perspective, remote sensing-guided investigation reduced field diesel consumption, drilling waste production, and site investigation duration by 42%. Furthermore, identifying zones with degraded shear strength (TPH-impacted areas) prior to heavy excavation equipment deployment significantly mitigates operational geotechnical risks, such as slope instability or equipment bogging.

LIMITATIONS

Despite its demonstrated advantages, remote sensing-assisted site investigation possesses key limitations:

- Penetration Depth Constraints: Optical VNIR-SWIR sensing is inherently restricted to surface and skin-depth observations (0–5 cm depth). Subsurface contaminant mapping relies on statistical geostatistical extrapolation or fusion with invasive soundings.
- Environmental Interference: High surface moisture (>25% gravimetric water content), dense vegetation cover (NDVI > 0.6), and organic litter attenuate soil spectral features, requiring advanced canopy unmixing models.
- Sensor Cost and Processing Complexity: High-resolution UAV hyperspectral systems involve high capital expenditure and specialized spectroscopic processing expertise.

FUTURE SCOPE

Future research should focus on integrating multi-sensor geophysical data—such as Ground Penetrating Radar (GPR) and Electrical Resistivity Tomography (ERT)—with optical remote sensing through deep learning multi-modal architectures. Fusing surface hyperspectral data with 3D geophysical subsurface resistivity tomograms will enable true 3D spatial modeling of contaminant plumes. Furthermore, developing operational satellite constellations with real-time hyperspectral analytics will facilitate continuous monitoring of active industrial sites and post-remediation validation.

CONCLUSION

This study established a comprehensive, sustainable remote sensing-assisted framework for characterizing contaminated soils in geotechnical site investigations. Integrating satellite multispectral data, UAV hyperspectral imaging, machine learning regression (RFR, 1D-CNN), and geotechnical CPTu soundings enabled accurate non-destructive mapping of heavy metals and petroleum hydrocarbons. The integrated approach reduced physical sampling

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requirements by 42%, lowered investigation carbon footprints, and identified critical geotechnical property degradations essential for safe remediation design. Remote sensing-assisted pre-screening represents a transformative approach for sustainable brownfield redevelopment and geoenvironmental engineering.

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