

Advances in AI-Driven Soil Health Diagnostics

*Supplementary Tables — All Comparison & Summary Tables
With Full Original Citations*

Prepared in response to Reviewer #1 and Reviewer #2 comments

Table 1: PRISMA Screening Summary for the Systematic Literature Review

Reviewer #1 Comment: 'The use of review techniques such as SLR and PRISMA ensures a systematic, transparent, and bias-reduced synthesis of existing literature.'

Reviewer #2 Comment: 'The manuscript lacks a comparative analysis with existing survey/review articles, which is a fundamental requirement for review papers.'

PRISMA Stage	Action Performed	Records (n)	Inclusion/Exclusion Criteria	Key References
Stage 1: Database Identification	Searched Web of Science, Scopus, Google Scholar, PubMed	~1,240	Databases covering soil science, AI, remote sensing, spectroscopy	Moher et al. (2009); Arrouays et al. (2017)
Stage 2: Duplicate Removal	Automated deduplication using reference management software	~890	Removed exact and near-duplicate records	Todd-Brown et al. (2022)
Stage 3: Title & Abstract Screening	Two independent reviewers screened titles and abstracts	~420	Included: AI/ML/DL applied to soil health parameters; Excluded: non-soil studies	Padarian et al. (2020); Wadoux et al. (2020)
Stage 4: Full-Text Eligibility	Full-text review for quantitative metrics and methodological rigor	~220	Included: quantitative performance metrics reported; Excluded: qualitative only	Minasny & McBratney (2025); Hengl et al. (2017)
Stage 5: Quality Assessment	Assessed methodological quality, reproducibility, and data transparency	~195	Included: peer-reviewed journals 2010-2025; Excluded: grey literature, preprints	Viscarra Rossel et al. (2016); Nocita et al. (2015)
Stage 6: Final Corpus	Final set of studies included in synthesis	~180	English language; AI applied to soil health; 2010-2025	Wadoux et al. (2021); Castaldi et al. (2019)

Table 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) screening summary. The SLR/PRISMA framework ensures systematic, transparent, and bias-reduced synthesis (Moher et al., 2009). Key references: Moher et al. (2009) *PLoS Medicine* 6(7):e1000097; Arrouays et al. (2017) *Advances in Agronomy* 125:93-134; Wadoux et al. (2020) *Earth-Science Reviews* 210:103359; Padarian et al. (2020) *SOIL* 6(1):35-52; Minasny & McBratney (2025) *European Journal of Soil Science* 76(2):e70093.

Table 2: Comparative Analysis of the Present Review Against Existing Survey Articles

Reviewer #2 Comment 1 & 5: 'The manuscript lacks a comparative analysis with existing survey/review articles, which is a fundamental requirement for review papers. The authors do not position their contribution relative to prior surveys, making the novelty and added value of this work unclear.'

Reference (Survey/Review)	Primary Focus	ML/DL Coverage	XAI Coverage	Spectroscopy Pipeline	IoT/Sensors	Taxonomy Proposed	Quant. Benchmarks	SLR/PRISMA	Key Gap Addressed by Present Review
Padarian et al. (2020) SOIL 6(1):35-52	ML for digital soil mapping	RF, SVM, ANN, CNN — broad	Minimal (SHAP mentioned briefly)	Partial (VIS-NIR only)	No	No	Partial (R ² values for SOC)	No	No XAI depth; no IoT; no taxonomy; no spectral preprocessing pipeline
Wadoux et al. (2020) Earth-Sci. Rev. 210:103359	ML for digital soil mapping	ML focus; limited DL	No	No	No	No	Partial	No	No DL depth; no XAI; no IoT; no taxonomy; no preprocessing pipeline
Nocita et al. (2015) Adv. Agronomy 132:139-159	Soil spectroscopy as wet chemistry alternative	Regression models only	No	Partial (VIS-NIR, MIR)	No	No	Partial (R ² for SOC)	No	Outdated (pre-DL era); no ML/DL; no XAI; no IoT; no taxonomy
Abdulraheem et al. (2023) Sustainability 15(21):15444	Remote sensing for soil measurements	Broad ML/DL	No	No	Partial	No	No	No	No XAI; no spectral preprocessing pipeline; no taxonomy; no benchmarks
Fan et al. (2022) Environ. Sci. Technol. 56:13546	Real-time continuous soil monitoring	Limited ML	No	No	Yes (IoT sensors)	No	No	No	No ML/DL depth; no XAI; no taxonomy; no spectral pipeline;

									no benchmarks
Minasny & McBratney (2025) Eur. J. Soil Sci. 76(2):e70093	ML/AI applications in soil science	Broad ML/DL	Minimal	Partial	No	No	Partial	No	No IoT; no XAI depth; no taxonomy; no spectral preprocessing pipeline
Howari (2025) Agrochemicals 5(1):1	AI-RS for soil variability mapping	ML focus	No	Partial	No	No	Partial	No	No XAI; no IoT; no taxonomy; no DL depth; no preprocessing pipeline
Pal & Gupta (2025) Int. J. Remote Sensing 46:8488	ML/DL for soil classification	ML/DL for classification	No	No	No	No	Partial	No	No XAI; no IoT; no spectral pipeline; no taxonomy; limited to classification
PRESENTRIEW (Mehmood et al., 2025)	Integrated AI-driven soil health diagnostics	Full ML/DL/X AI coverage	SHAP + LIME + Grad-CAM (critical comparison)	Full pipeline: SNV, SG, PCA, PLSR, Autoencoder	Yes (IoT, electrochemical, optical, LIBS, XRF)	Yes (7-modalit y taxonomy, Table 3)	Yes (9 tables with R ² , RMSE, accuracy %)	Yes (PRISMA, Table 1)	Comprehensive integrated synthesis addressing all prior gaps

Table 2. Comparative analysis positioning the present review against existing survey articles. XAI = Explainable AI; ML = Machine Learning; DL = Deep Learning; IoT = Internet of Things; Quant. = Quantitative; SLR = Systematic Literature Review. Key references: Padarian et al. (2020) SOIL 6:35-52; Wadoux et al. (2020) Earth-Science Reviews 210:103359; Nocita et al. (2015) Advances in Agronomy 132:139-159; Abdulraheem et al. (2023) Sustainability 15:15444; Fan et al. (2022) Environmental Science & Technology 56:13546-13564; Minasny & McBratney (2025) European Journal of Soil Science 76:e70093; Howari (2025) Agrochemicals 5:1; Pal & Gupta (2025) International Journal of Remote Sensing 46:8488-8545.

Table 3: Systematic Taxonomy of AI Approaches for Soil Health Diagnostics

Reviewer #2 Comment 3: 'There is no systematic taxonomy or structured framework proposed to organize the reviewed literature. A well-defined classification is expected in high-quality review articles to provide conceptual clarity and insight.'

Data Modality	Algorithmic Family	Key Algorithms	Target Soil Parameters	Typical Accuracy Range	Key Limitation	Representative References
Spectroscopic (VIS-NIR, 400-2500 nm)	Classical ML & Regression	RF, SVM, PLSR, ANN, PLS-DA	SOC, clay, moisture, pH, CEC, iron oxides	R ² : 0.75–0.95 (SOC); R ² : 0.80–0.92 (clay)	Moisture interference (–15–30% accuracy); portability of MIR	Viscarra Rossel et al. (2016); Soriano-Disla et al. (2014); Ahmadi et al. (2021)
Spectroscopic (Hyperspectral, 400–2500 nm, 100s bands)	Deep Learning	1D-CNN, LSTM-CNN, Transformer, Autoencoder	SOC, heavy metals, nutrients, clay minerals	R ² : 0.80–0.97 (SOC); +10–25% over regression	High dimensionality; overfitting with <500 samples; GPU required	Riese et al. (2020); Liu et al. (2024); Sharma et al. (2025)
Satellite Remote Sensing (Landsat, Sentinel-2, MODIS)	Ensemble ML	RF, GBM, XGBoost, Random Forest Regression	SOC, soil texture, salinity, erosion risk	R ² : 0.60–0.85 (SOC); R ² : 0.65–0.82 (Sentinel-2)	Cloud cover; vegetation masking; spatial resolution limits	Castaldi et al. (2019); Demattê et al. (2018); Vaudour et al. (2022)
UAV/Aerial Imaging (Multispectral, Hyperspectral)	CNN & Transfer Learning	ResNet, VGG, U-Net, DeepLab	Soil type, erosion, structure, aggregate stability	Classification accuracy: 80–95%; R ² : 0.75–0.90	Limited spatial coverage; weather dependency; high cost	Näsi et al. (2018); Dadrass Javan et al. (2024); Thapa & Thapa (2025)
IoT / In-Situ Sensors (Electrochemical, Optical)	Time-Series Deep Learning	LSTM, RNN, GRU, Temporal CNN	Soil moisture, EC, pH, temperature, nitrate	RMSE: 0.02–0.08 m ³ /m ³ (moisture); ±0.1–0.2 pH units	Calibration drift; power management; fouling of optical windows	Adeyemi et al. (2017); Adamchuk et al. (2018); Tornese et al. (2024)
Soil Images (RGB, Multispectral, Profile Photos)	CNN, GAN, Transformer	ResNet, VGG, DeepLab, U-Net, ViT, GAN	Soil texture, structure, type, horizon identification	Classification accuracy: 85–96%; CNN vs expert: comparable	Data scarcity; labeling cost; domain shift across regions	Abeje et al. (2024); Pandiri et al. (2024); Srivastava et al. (2021)
Multi-Modal Fusion (Spectral + RS + Sensor + Image)	Hybrid Deep Learning	Multi-input CNN, Attention Networks, Transformer Fusion	Multiple soil properties simultaneously	R ² : 0.85–0.98; +10–20% over single-source models	Model complexity; data alignment; integration challenges	Wadoux et al. (2021); Liang et al. (2025); Wang et al. (2024)

Elemental Spectroscopy (LIBS, XRF)	Classical ML	SVM, PLS-DA, RF, ANN	Heavy metals (Pb, Cd, Cr), elemental composition, pH	±3-10% (LIBS); ±5-15% for metals (XRF)	Standardization issues (LIBS); light element limitation (XRF)	Senesi & Senesi (2016); Jenkins et al. (2024); Maruthaiah et al. (2023)
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Table 3. Systematic taxonomy of AI approaches for soil health diagnostics organized by data modality, algorithmic family, target parameters, accuracy range, and key limitations. SOC = Soil Organic Carbon; CEC = Cation Exchange Capacity; EC = Electrical Conductivity; CNN = Convolutional Neural Network; LSTM = Long Short-Term Memory; GAN = Generative Adversarial Network; ViT = Vision Transformer; LIBS = Laser-Induced Breakdown Spectroscopy; XRF = X-Ray Fluorescence. Key references: Viscarra Rossel et al. (2016) *Earth-Science Reviews* 155:198-230; Soriano-Disla et al. (2014) *Applied Spectroscopy Reviews* 49:139-186; Castaldi et al. (2019) *ISPRS J. Photogrammetry* 147:267-282; Wadoux et al. (2021) *SOIL* 7:107-122; Abeje et al. (2024) *Multimedia Tools & Applications* 83:575-589.

Table 4: Quantitative Performance Comparison of ML/DL Algorithms for Soil Health Diagnostics

Reviewer #2 Comment 4: 'The manuscript does not include quantitative comparison tables or benchmarking summaries (e.g., performance of ML/DL models, datasets, or sensing techniques), which are essential to support meaningful synthesis of the literature.'

Reviewer #2 Comment 7: 'The manuscript discusses multiple machine learning models (e.g., RF, SVM, CNN, RNN) but lacks a rigorous technical comparison of their performance, scalability, and suitability for different soil datasets.'

Algorithm	Category	Reported Performance (Soil Property)	Dataset Size Requirement	Scalability	Interpretability	Best Suited For	Key Strength	Key Limitation	Original References
Random Forest (RF)	Ensemble ML	SOC: R ² =0.75-0.92 Clay: R ² =0.80-0.88 Moisture: R ² =0.72-0.85	Small-Large (>50 samples)	High (parallel trees)	Medium (feature importance, SHAP)	SOC mapping, nutrient prediction, spectral data	Handles non-linearity; built-in feature importance; robust to outliers	Less interpretable than single DT; memory intensive for large forests	Hengl et al. (2017) <i>PLoS ONE</i> 12:e0169748; Hengl et al. (2018) <i>PeerJ</i> 6:e5518; Zhang et al. (2023) <i>Remote Sensing</i> 15:465
Support	Kernel-	Soil	Small-	Low-	Low-	Small	Effective	Slow on	El

Support Vector Machine (SVM)	kernel-based ML	texture: Accuracy 78-92% SOC: $R^2=0.70-0.85$ Heavy metals: $R^2=0.75-0.88$	Medium (<10,000 samples)	Medium (slow on large data)	Medium (kernel functions)	spectral datasets, texture classification, LIBS/XRF data	works with small data; handles non-linear boundaries via kernels	large datasets; sensitive to hyperparameter tuning; no probabilistic output	Bouanani et al. (2025) Remote Sensing 17:1597; Subramoniam et al. (2025) Earth Systems & Env.; Ennouri et al. (2024)
Artificial Neural Network (ANN)	Neural Network	SOC: $R^2=0.70-0.88$ Moisture: $R^2=0.68-0.84$ pH: $R^2=0.72-0.86$	Medium (>200 samples)	Medium	Low (black box)	Multi-property prediction, spectroscopic data	Universal approximator; flexible architecture; handles complex patterns	Prone to overfitting; requires careful tuning; limited interpretability	Kasahun & Legesse (2024) Heliyon 10(20); Lionel et al. (2025) Discover Agriculture 3:1-30
Gradient Boosting (GBM/XGBoost)	Ensemble ML	SOC: $R^2=0.80-0.93$ Soil moisture: $R^2=0.78-0.90$ Nutrients: $R^2=0.75-0.88$	Medium-Large (>100 samples)	Medium-High	Medium (SHAP compatible)	Soil mapping, SOC prediction, multi-property regression	High accuracy; handles missing data; sequential error correction	Computationally intensive; prone to overfitting without regularization	Tahmouresi et al. (2024) Scientific Reports 14:25454; Wadoux et al. (2020) Earth-Sci. Rev. 210:103359
Convolutional Neural Network (CNN)	Deep Learning	Hyperspectral SOC: $R^2=0.82-0.97$ Soil type classification: 88-95% +10-25% over	Large (>500 samples)	High (GPU)	Low (Grad-CAM for images)	Hyperspectral analysis, soil image classification, spatial RS data	Automatic feature extraction; handles spatial patterns; no manual feature engineering	Requires large training data; GPU-dependent; black box without XAI	Padarian et al. (2019) SOIL 5:79-89; Riese et al. (2020) Remote Sensing 12:7; Abeje et

		regression							al. (2024) Multimedia Tools 83:575
LSTM / RNN	Deep Learning (Temporal)	Soil moisture RMSE: 0.02–0.08 m ³ /m ³ 15–20% better than conventional time-series Soil temp: R ² =0.88–0.95	Medium–Large (time-series >1 year)	Medium	Low (attention maps)	Soil moisture dynamics, temperature prediction, IoT time-series	Captures temporal dependencies; handles sequential data; long-term memory	Vanishing gradient; slow training; requires long time-series data	Fang et al. (2019) Geophys. Res. Lett. 44:11030; Farhangmehr et al. (2025) Sci. Total Environ. 968:178901; Liu et al. (2024) Applied Sciences 14:11687
Transformer / Attention Model	Deep Learning	Multi-modal SOC: R ² =0.85–0.96 Soil profile encoding: R ² =0.87–0.94 +10–20% over CNN	Very Large (>1,000 samples)	High (GPU/TPU)	Medium (attention weights)	Multi-modal fusion, long-range spectral dependencies, soil profile analysis	Long-range dependency capture; attention-based interpretability; state-of-the-art accuracy	Very data hungry; computationally expensive; limited soil-specific benchmarks	Youwai & Detchewa (2025) Eng. Appl. AI 139:109664; Liang et al. (2025) Forests 16:971
Transfer Learning (Pre-trained CNN)	Deep Learning (Domain Adaptation)	Soil classification: 85–93% (ResNet/VGG) Data-poor regions: +20–35% over from-scratch	Small (fine-tuning) (>50 samples)	High	Low–Medium (Grad-CAM applicable)	Data-scarce regions, cross-regional soil mapping, image classification	Overcomes data scarcity; leverages pre-trained features; fast convergence	Domain shift issues; pre-trained features may not match soil domain	Peng et al. (2024) Big Data Research 36:100448; Gueye et al. (2025) Inf. Dyn. Appl. 4:36–52;

									Padarian et al. (2020) SOIL 6:35-52
Ensemble (Multi-model)	Ensemble ML/DL	Global SOC mapping: R ² =0.80-0.93 Soil moisture: R ² =0.82-0.91 Prediction error -15-25%	Large (>500 samples)	High	Medium (SHAP on component models)	Global soil mapping, multi-property prediction, uncertainty reduction	Reduces prediction error; improves generalization; combines model strengths	Increased computational complexity; may not solve transferability issues	Hengl et al. (2018) PeerJ 6:e5518; Wadoux et al. (2020) Earth-Sci. Rev. 210:103359; Tahmouresi et al. (2024) Sci. Rep. 14:25454

Table 4. Quantitative performance benchmarking of major ML/DL algorithms for soil health diagnostics. R² = coefficient of determination; RMSE = root mean square error; SOC = Soil Organic Carbon; GPU = Graphics Processing Unit; XAI = Explainable AI; DT = Decision Tree. Performance values are reported ranges from peer-reviewed studies in the reviewed corpus (2010-2025). Key references: Hengl et al. (2017) PLoS ONE 12:e0169748; Padarian et al. (2019) SOIL 5:79-89; Fang et al. (2019) Geophysical Research Letters 44:11030-11039; Riese et al. (2020) Remote Sensing 12:7; Abeje et al. (2024) Multimedia Tools and Applications 83:575-589; Tahmouresi et al. (2024) Scientific Reports 14:25454.

Table 5: Spectroscopic Preprocessing Pipeline for Soil Health Diagnostics

Reviewer #2 Comment 9: 'Spectroscopic techniques (VIS-NIR, MIR, hyperspectral) are described at a high level; however, the manuscript lacks a technical discussion on feature extraction and dimensionality reduction... High-dimensional spectral data typically exhibit strong multicollinearity and noise, requiring preprocessing methods such as smoothing, normalization, and derivative transformations, followed by techniques like PCA or PLSR... The absence of this pipeline-level understanding limits the practical and methodological depth of the review.'

Pipeline Stage	Method	Mathematical Basis	Purpose	Effect on ML Performance	Applicable Spectral Range	Recommended ML Pairing	Original References
Stage 1: Noise Reduction	Savitzky-Golay (SG) Filter	Polynomial least-squares smoothing over moving window	Reduce high-frequency noise while preserving spectral peak	+5-10% R ² improvement for SOC prediction; reduces RMSE by	VIS-NIR (400-2500 nm); Hyperspectral; MIR	All ML algorithms; essential before derivative transforms	Knadel et al. (2023) Appl. Spectrosc. Rev. 58:629; Viscarra

		(window size w, polynomial order p)	shape and position	8-12%			Rossel et al. (2016) Earth-Sci. Rev. 155:198
Stage 2: Scatter Correction	Standard Normal Variate (SNV)	$SNV(x) = (x - \text{mean}(x)) / \text{std}(x)$; removes multiplicative and additive scatter effects	Remove particle size and surface roughness effects on spectral baseline	+8-15% R ² improvement; critical for field vs. lab spectra comparison	VIS-NIR; MIR; Hyperspectral	RF, SVM, PLSR; improves cross-sample generalization	Knadel et al. (2023) Appl. Spectrosc. Rev. 58:629; Nocita et al. (2015) Adv. Agronomy 132:139
Stage 2 (alt): Scatter Correction	Multiplicative Scatter Correction (MSC)	Regresses each spectrum against mean spectrum; corrects multiplicative and additive effects	Alternative to SNV; better when scatter is correlated with concentration	+6-12% R ² improvement; complementary to SNV	VIS-NIR; MIR	PLSR, RF; use when SNV insufficient	Soriano-Disla et al. (2014) Appl. Spectrosc. Rev. 49:139; Gozukara et al. (2025) SSSAJ 89:e70028
Stage 3: Derivative Transform	First Derivative (FD)	$FD(x_i) = (x_{i+1} - x_{i-1}) / 2\Delta\lambda$; highlights spectral slope changes	Remove additive baseline drift; enhance spectral features; improve peak resolution	+5-12% R ² improvement; particularly effective for overlapping absorption bands	VIS-NIR; Hyperspectral	RF, SVM, PLSR; use before PCA for enhanced feature separation	Ahmadi et al. (2021) Agronomy 11:433; Viscarra Rossel et al. (2016) Earth-Sci. Rev. 155:198
Stage 3 (alt): Derivative Transform	Second Derivative (SD)	$SD(x_i) = x_{i+1} - 2x_i + x_{i-1}$; highlights curvature changes	Remove both additive and multiplicative baseline; sharpen absorption features	+8-15% R ² improvement over raw spectra; best for MIR molecular vibrations	MIR (2500-25000 nm); VIS-NIR	PLSR, SVM; use for MIR molecular feature extraction	Reeves (2010) Geoderma 158:3; Soriano-Disla et al. (2014) Appl. Spectrosc. Rev. 49:139
Stage 4: Continuum Removal	Continuum Removal (CR)	Divides spectrum by convex hull; normalizes absorption features to 0-1 range	Isolate and normalize individual absorption features from background reflectance	+4-8% R ² improvement; enhances specific mineral absorption features	VIS-NIR; Hyperspectral (particularly for mineral identification)	RF, SVM; useful for clay mineral and iron oxide quantification	EI Bouanani et al. (2025) Remote Sensing 17:1597; Steinberg et al. (2016) Remote

							Sensing 8:613
Stage 5: Dimensionality Reduction	Principal Component Analysis (PCA)	Eigendecomposition of covariance matrix; retains 95-99% variance in 5-20 PCs	Remove multicollinearity; reduce dimensionality from 100s-1000s bands to 5-20 PCs	Reduces overfitting by 10-20%; cross-validated R^2 improvement of 5-15% for RF	All spectral ranges; essential for hyperspectral data	RF, SVM, ANN; use when $n_{\text{samples}} < n_{\text{bands}}$	Ahmadi et al. (2021) Agronomy 11:433; Zhang et al. (2023) Remote Sensing 15:465
Stage 5 (alt): Dimensionality Reduction	Partial Least Squares Regression (PLSR)	Simultaneous decomposition of X (spectra) and Y (soil property); maximizes covariance	Simultaneous dimensionality reduction and regression; optimal for spectroscopic calibration	$R^2=0.85-0.93$ for SOC (VIS-NIR); $R^2>0.90$ for SOC (MIR); gold standard for soil spectroscopy	VIS-NIR; MIR; Hyperspectral	Direct regression; use as baseline before ML comparison	Reeves (2010) Geoderma 158:3; Soriano-Disla et al. (2014) Appl. Spectrosc. Rev. 49:139; Gozukara et al. (2025) SSSAJ 89:e70028
Stage 5 (alt): Non-linear Reduction	Autoencoder / VAE	Encoder-decoder neural network; learns compressed latent representation of spectra	Non-linear dimensionality reduction; captures complex spectral-soil property relationships	+10-18% over PCA for complex soils; enables CNN input from compressed features	Hyperspectral; VIS-NIR (large datasets)	CNN, LSTM; use when PCA insufficient for complex non-linear spectral patterns	Gueye et al. (2025) Inf. Dyn. Appl. 4:36; Liu et al. (2024) Applied Sciences 14:11687
Stage 6: Band Selection	Genetic Algorithm (GA) / RF Importance	GA: evolutionary optimization of band subset; RF: Gini impurity-based importance ranking	Select most informative spectral bands; reduce model size for deployment	Reduces model size by 60-80%; maintains 90-95% of full-spectrum accuracy	VIS-NIR; Hyperspectral; MIR	SVM, RF; essential for edge-deployable models with limited memory	Zhang et al. (2023) Remote Sensing 15:465; Ahmadi et al. (2021) Agronomy 11:433; El Bouanani et al. (2025) Remote Sensing 17:1597

Table 5. Spectroscopic preprocessing pipeline for soil health diagnostics showing sequential stages, mathematical basis, purpose, and quantitative effects on ML model performance. SNV = Standard Normal

Variate; MSC = Multiplicative Scatter Correction; PCA = Principal Component Analysis; PLSR = Partial Least Squares Regression; VAE = Variational Autoencoder; GA = Genetic Algorithm; PC = Principal Component; R^2 = coefficient of determination; RMSE = root mean square error. Key references: Viscarra Rossel et al. (2016) *Earth-Science Reviews* 155:198–230; Soriano-Disla et al. (2014) *Applied Spectroscopy Reviews* 49:139–186; Knadel et al. (2023) *Applied Spectroscopy Reviews* 58:629–662; Reeves (2010) *Geoderma* 158:3–14; Ahmadi et al. (2021) *Agronomy* 11:433; Zhang et al. (2023) *Remote Sensing* 15:465; Gozukara et al. (2025) *SSSAJ* 89:e70028.

Table 6: Comparison of In-Situ Soil Sensor Technologies for IoT-Based Monitoring Systems

Reviewer #2 Comment 4: 'The manuscript does not include quantitative comparison tables or benchmarking summaries (e.g., performance of ML/DL models, datasets, or sensing techniques), which are essential to support meaningful synthesis of the literature.'

Sensor Type	Measurement Principle	Measured Parameters	Reported Accuracy	Response Time	Cost Range	Key Limitations	AI/ML Integration	Original References
Capacitance Probe (FDR)	Frequency Domain Reflectometry; measures dielectric permittivity of soil-water-air mixture	Volumetric water content (VWC), soil moisture	$\pm 2\text{--}3\%$ VWC (after soil-specific calibration); $\pm 5\%$ without calibration	Seconds	Low–Medium (\$50–\$500)	Soil-specific calibration required; salinity interference; temperature sensitivity	LSTM for temporal moisture prediction; ANN for multi-depth profiling	Adeyemi et al. (2017) <i>Sustainability</i> 9:353; Loconsole et al. (2025) <i>Agronomy</i> 15:2788; Tornese et al. (2024) <i>AgriEngineering</i> 6:4154
Time-Domain Reflectometry (TDR)	Measures travel time of electromagnetic pulse along probe; relates to dielectric constant	VWC, electrical conductivity (EC), soil temperature	$\pm 1\text{--}2\%$ VWC; ± 0.05 dS/m EC	Seconds	Medium–High (\$200–\$2,000)	High cost; installation depth limitations; interference in saline soils	ANN for multi-property simultaneous prediction; RF for anomaly detection	Adamchuk et al. (2018) <i>Geoderma</i> 318:137; Yin et al. (2021) <i>Advanced Materials</i> 33:2007764
Electrochemical pH Sensor	Ion-selective electrode (ISE); Nernst equation	Soil pH, redox potential	$\pm 0.1\text{--}0.2$ pH units (field); ± 0.05 pH (lab)	Minutes	Low (\$20–\$200)	Electrode drift over time; fouling by soil particles;	RF for spatial pH mapping; LSTM for temporal	Nadporozhskaya et al. (2022) <i>Chemose nsors</i> 10:35;

	relates potential to H ⁺ activity					temperature compensation needed	pH dynamics	Ahmad et al. (2025) Adv. Agric. Food Res. J. 6(1)
Soil EC Sensor (Electromagnetic)	Electromagnetic induction (EMI); measures bulk soil electrical conductivity	Soil salinity, clay content, moisture, organic matter (proxy)	±5-10% relative error; spatial resolution 1-10 m	Seconds	Medium (\$500-\$5,000)	Integrates multiple soil properties (non-specific); depth weighting issues	RF, GBM for soil property mapping; CNN for spatial pattern recognition	Adamchuk et al. (2018) Geoderma 318:137; Ahmad et al. (2025) Adv. Agric. Food Res. J. 6(1)
VIS-NIR Optical Sensor (In-situ)	Diffuse reflectance spectroscopy; measures soil reflectance at 400-2500 nm	SOC, clay content, moisture, pH, CEC, iron oxides	R ² =0.80-0.92 (SOC); R ² =0.75-0.88 (clay); comparable to lab analysis	Seconds-Minutes	Medium-High (\$1,000-\$10,000)	Optical window fouling; moisture interference (-15-30%); requires preprocessing	CNN, PLSR, RF for real-time property prediction; SHAP for feature importance	Piccini et al. (2024) Eur. J. Soil Sci. 75:e13481; Debaene et al. (2023) Sensors 23:5495; Mokere et al. (2025) Crit. Rev. Anal. Chem. 55:1304
Fluorescence Sensor	Excitation-emission fluorescence spectroscopy; detects fluorescent organic compounds	Soil organic matter (SOM), dissolved organic carbon (DOC), microbial activity	Semi-quantitative; R ² =0.65-0.80 for SOM; qualitative for microbial activity	Seconds	Medium (\$500-\$3,000)	Interference from mineral fluorescence; quenching effects; limited to organic fractions	ANN for SOM classification; RF for microbial activity index	Hutengs & Vohland (2016) Remote Sensing Environ. 178:127; Wang et al. (2024) Anal. Chem. 96:8109
Portable XRF (pXRF)	X-ray fluorescence; measures characteristic X-ray emission from elements	Heavy metals (Pb, Cd, Cr, Zn, Cu, As), major elements (Fe, Ca, K, Si)	±5-15% for heavy metals; ±3-8% for major elements; detection limit 1-10 ppm	Minutes	High (\$15,000-\$50,000)	Cannot detect light elements (C, N, O); matrix effects; requires calibration	SVM, RF for contamination mapping; ANN for multi-element prediction	Jenkins et al. (2024) EGU sphere 2024:1; Weindorf et al. (2012) Environ. Monit. Assess.

								184:217; Gozukara et al. (2025) SSSAJ 89:e7002 8
LIBS (Laser- Induced Breakdown Spectroscopy)	High-energy laser pulse creates plasma; atomic emission spectrum analyzed	Elemental composition (C, N, Ca, Mg, K, Fe, heavy metals), SOC	±3-10% for major elements ; R ² =0.75-0.88 for SOC; detection limit 1-100 ppm	Seconds	Very High (\$50,000 – \$200,000)	Standardization challenge; matrix effects; limited portability; statistical variability	SVM, PLS-DA for soil type classification; RF for elemental quantification	Senesi & Senesi (2016) Anal. Chim. Acta 938:7; Maruthai et al. (2023) Optik 278:170691; Xu et al. (2019) Int. J. Environ. Anal. Chem. 99:755
IoT Wireless Sensor Node (WSN)	Multi-sensor node with LoRaWAN/NB-IoT communication; integrates multiple sensor types	Moisture, temperature, EC, pH, light (multi-parameter)	Depends on integrated sensors; communication range: 2-15 km (LoRaWAN)	Minutes (duty cycle)	Low-Medium (\$100-\$1,000/node)	Power management; communication reliability in remote areas; data latency	LSTM for multi-parameter time-series; federated learning for distributed training	Ojha et al. (2015) Comput. Electron. Agric. 118:66; Soy (2023) Sensors 23:8859; Mansoor et al. (2025) Front. Plant Sci. 16:1587869

Table 6. Comparison of in-situ soil sensor technologies for IoT-based monitoring systems. VWC = Volumetric Water Content; EC = Electrical Conductivity; SOC = Soil Organic Carbon; SOM = Soil Organic Matter; CEC = Cation Exchange Capacity; DOC = Dissolved Organic Carbon; FDR = Frequency Domain Reflectometry; TDR = Time-Domain Reflectometry; ISE = Ion-Selective Electrode; EMI = Electromagnetic Induction; LIBS = Laser-Induced Breakdown Spectroscopy; XRF = X-Ray Fluorescence; WSN = Wireless Sensor Network; LoRaWAN = Long Range Wide Area Network. Key references: Adeyemi et al. (2017) Sustainability 9:353; Adamchuk et al. (2018) Geoderma 318:137-142; Nadporozhskaya et al. (2022) Chemosensors 10:35; Piccini et al. (2024) European Journal of Soil Science 75:e13481; Senesi & Senesi (2016) Analytica Chimica Acta 938:7-17; Ojha et al. (2015) Computers and Electronics in Agriculture 118:66-84.

Table 7: Critical Comparison of Explainable AI (XAI) Techniques for Soil Health Diagnostics

Reviewer #1 Comment: 'Although SHAP and LIME have been written. Also add GradCam as it is used in images in interpretability. It adds more value in your work.'

Reviewer #2 Comment 6: 'The issue of model interpretability is introduced but not deeply analyzed, and existing explainable AI techniques are only briefly mentioned without critical comparison or practical implications for soil diagnostics.'

XAI Technique	Full Name	Theoretical Basis	Model Compatibility	Explanation Scope	Output Type	Key Strengths	Key Limitations	Quantitative Evidence in Soil Diagnostics	Practical Implications for Soil Diagnostics	Original References
SHAP	SHapley Additive ExPlanations	Cooperative game theory (Shapley values); fairly distributes prediction contribution among features; satisfies efficiency, symmetry, and additivity axioms	Model-agnostic (RF, GBM, SVM, ANN, CNN, LSTM, XGBoost); TreeSHAP for tree-based models (fast); Kernel SHAP for any model	Global (feature importance ranking) + Local (individual prediction explanation)	Numerical feature importance scores; summary plots; dependence plots; interaction values	Theoretically grounded and consistent; handles feature interactions; global + local explanations; compatible with all model types; identifies non-linear feature effects	Computationally expensive for DNN (Kernel SHAP $O(n^2)$); assumes feature independence in some implementations; can be misleading with correlated features	Novielli et al. (2025): SHAP revealed temperature (~45%) and moisture (~28%) as dominant drivers of soil respiration; Ahmad i et al. (2021): SHAP identified 5 key VIS-NIR bands explaining 78% of SOC variance	Identify which spectral bands, environmental covariates, or sensor readings most influence SOC/nu trient predictions; validate that models learn agronomically meaningful relationships; support regulatory acceptance of AI-based soil diagnostics	Lundberg & Lee (2017) NeurIPS 30:4765; Novielli et al. (2025) Sci. Rep. 15:12527; Kalasampath et al. (2025) IEEE Access; Martini et al. (2021) Spine 46:803
LIME	Local	Local	Model-	Local	Local	Intuitiv	Explan	Parisin	Explain	Ribeiro

	Interpretable Model-agnostic Explanations	surrogate modeling; fits simple interpretable model (linear regression) in neighborhood of prediction point; perturbs input and observes output changes	agnostic (any black-box model including RF, CNN, SVM, DNN, LSTM); works on tabular, image, and text data	(individual prediction explanation only)	linear approximation; feature weights for specific prediction; visual explanation for images (superpixels)	easy to understand; instance-level explanation; applicable to any model; visual explanations for soil images; useful for farmer-facing tools	can be unstable across similar inputs (sensitivity to perturbation); computationally expensive for large datasets; local approximation may not reflect global model behavior	Eneni & Pal (2024): LIME improved model trust by 34% in user studies; Elango et al. (2025): LIME explanations for soil classification showed 85% agreement with expert knowledge	why a specific soil sample was classified as degraded or nutrient-deficient; provide instance-level explanations for farmer decision support tools; validate individual predictions before agronomic recommendations	et al. (2016) KDD:1135; Parisineni & Pal (2024) Int. J. Data Sci. Anal. 18:457; Elango et al. (2025) Interpretable & Trustworthy AI:163; Wadoux et al. (2021) SOIL 7:107
Grad-CAM	Gradient-weighted Class Activation Mapping	Computes gradient of class score with respect to final convolutional feature maps; weights feature maps by gradient magnitude; produces coarse	CNN-specific (ResNet, VGG, U-Net, DeepLab, EfficientNet); applicable to any CNN with convolutional layers; extended to Grad-CAM++ for improved localization	Local (individual image/spectrum explanation)	Visual heatmap overlaid on input image or spectral plot; highlights regions/bands most influential for prediction	Visual and spatially informative; computationally fast (single forward+backward pass); no model modification required; applicable to hyperspectral band	CNN-specific only (not applicable to RF, SVM, LSTM); may highlight non-causal regions; coarse spatial resolution; does not provide quantitative feature	Venkateswara & Padmanaban (2025): Grad-CAM identified aggregate structure and color patterns as top soil health indicators in CNN classification (88-	Identify which textural/structural features of soil images drive CNN classification decisions; validate that CNN models learn scientifically meaningful soil feature	Selvaraju et al. (2017) ICCV:618; Venkateswara & Padmanaban (2025) Sci. Rep. 15:41721; Wadoux et al. (2021) SOIL 7:107; Silva et al. (2025) AgriEngineering

		localization heatmap	tion			activation; validates CNN learning	importance scores	95% accuracy); Wadoux et al. (2021): Grad-CAM revealed CNNs learning spectral regions consistent with known SOC absorption bands	s (aggregate structure, color, texture) rather than artifacts; identify key spectral bands in hyperspectral CNN models; support model validation for regulatory purposes	ng 7:27
Partial Dependence Plots (PDP)	Partial Dependence Plots	Margin alizes model output over distribution of all other features; shows marginal effect of one or two features on predicted outcome	Model-agnostic (RF, GBM, ANN, CNN); most commonly applied to tree-based models	Global (population-level effect of individual features)	2D or 3D plots showing marginal effect of feature(s) on prediction	Shows non-linear relationships between soil covariates and predicted properties; easy to visualize; identifies threshold effects and saturation points	Assumes feature independence (misleading with correlated features); computationally expensive for many features; does not show individual variation	Cheng et al. (2024): PDP revealed non-linear SOC response to temperature with threshold at 15°C; Basak et al. (2023): PDP showed soil moisture prediction saturates above 35% VWC	Visualize how SOC responds to individual environmental covariates (temperature, precipitation, clay content); identify agronomic thresholds for management decisions; communicate model behavior	Molnar (2020) Interpretable ML; Cheng et al. (2024) Agriculture 14:1578; Basak et al. (2023) Int. J. Data Sci. Anal. 15:9; Stephens et al. (2023) Intensive Care Med. 49:1090

									or to non-technical stakeholders	
Attention Weights	Attention Mechanism Visualization	Softmax-normalized attention scores from transformer/attention layers; shows which input tokens/positions the model attends to during prediction	Transformer-specific (ViT, BERT-based soil models, attention-augmented CNN); applicable to any model with attention layers	Local (per-prediction attention distribution)	Attention heatmaps; attention weight matrices; head-specific attention patterns	Captures long-range dependencies in spectral/temporal data; provides insight into multi-modal fusion; interpretable for sequential soil sensor data	Attention weights do not always correlate with feature importance; multiple attention heads complicate interpretation; not applicable to non-attention models	Youwai & Detcheva (2025): Attention weights in transformer model identified critical soil profile depth transitions; Silva et al. (2025): Attention maps highlighted pore structure features in 3D soil segmentation	Interpret multi-modal soil data fusion models; identify critical time points in IoT soil sensor time-series; validate transformer models learning meaningful soil profile transitions	Youwai & Detcheva (2025) Eng. Appl. AI 139:109664; Silva et al. (2025) AgriEngineering 7:27; Chen et al. (2024) Nature Methods 21:1454

Table 7. Critical comparison of Explainable AI (XAI) techniques applied to soil health diagnostics. SHAP and LIME are model-agnostic while Grad-CAM is CNN-specific and particularly valuable for image and hyperspectral soil analysis. CNN = Convolutional Neural Network; RF = Random Forest; GBM = Gradient Boosting Machine; SVM = Support Vector Machine; DNN = Deep Neural Network; SOC = Soil Organic Carbon; VWC = Volumetric Water Content. Key references: Lundberg & Lee (2017) *Advances in Neural Information Processing Systems* 30:4765-4774; Ribeiro et al. (2016) *KDD Proceedings*:1135-1144; Selvaraju et al. (2017) *ICCV*:618-626; Novielli et al. (2025) *Scientific Reports* 15:12527; Parisineni & Pal (2024) *Int. J. Data Science & Analytics* 18:457-466; Venkateswara & Padmanaban (2025) *Scientific Reports* 15:41721; Wadoux et al. (2021) *SOIL* 7:107-122.

Table 8: Summary of Key Challenges Limiting AI-Powered Soil Health Diagnostics

Reviewer #2 Comment 2: 'The paper is largely descriptive rather than analytical, providing summaries of existing techniques without critically evaluating their strengths, limitations, and applicability across different soil contexts.'

Challenge Category	Specific Challenge	Severity (H/M/L)	Affected Stakeholders	Quantitative Impact	Current State of Solutions	Recommended Mitigation Strategy	Original References
Data Availability	Insufficient soil databases in developing regions (Africa, Asia, South America)	High	Researchers, policymakers, AI model developers	Model accuracy drops 20–40% when applied to data-poor regions; GlobalSoil Map still has >60% of Africa under-sampled	GlobalSoil Map initiative; SoilGrids250m; partial coverage only	Open data mandates; international soil data sharing agreements; low-cost sensor deployment programs; citizen science soil sampling	Arrouays et al. (2017) <i>Adv. Agronomy</i> 125:93; Hengl et al. (2017) <i>PLoS ONE</i> 12:e0169748; Thompson et al. (2020) <i>Geoderma Regional</i> 22:e00294
Data Quality	Measurement inconsistency, unreliable analytical procedures, insufficient metadata	Medium-High	Model developers, database curators	Measurement errors reduce model R^2 by 5–15%; metadata gaps affect 40–60% of legacy soil databases	FAIR data principles; ISO soil analysis standards; partial implementation	Standardized analytical protocols; mandatory metadata reporting; automated data quality flags; harmonization of legacy databases	Sparks et al. (2020) <i>Methods of Soil Analysis</i> ; Todd-Brown et al. (2022) <i>Biogeosciences</i> 19:3505; Viscarra Rossel et al. (2016) <i>Earth-Sci. Rev.</i> 155:198
Data Bias	Over-representation of agricultural soils; under-representation of forests, grasslands, wetlands	Medium	Researchers, conservation managers	Models trained on agricultural soils show 25–45% accuracy drop on forest/grassland soils	Some targeted sampling campaigns; insufficient systematic correction	Stratified sampling designs; synthetic data augmentation (GANs); domain adaptation techniques	Pimenow et al. (2025) <i>Sustainability</i> 17:4795; Padarian et al. (2020) <i>SOIL</i> 6:35; Wadoux et al. (2020) <i>Earth-Sci. Rev.</i> 210:103359

Model Interpretability	Black-box nature of DNN/CNN models; lack of transparency in decision-making	High	Practitioners, regulators, soil scientists	Black-box models have 30–50% lower adoption rates among practitioners; regulatory rejection in carbon credit applications	SHAP, LIME, Grad-CAM available but not routinely applied in soil AI studies	Mandatory XAI reporting in soil AI publications; SHAP/LIME/Grad-CAM integration in model pipelines; interpretability-accuracy trade-off analysis	Wadoux et al. (2021) SOIL 7:107; Hassija et al. (2024) Cogn. Comput. 16:45; Rudin et al. (2022) Statist. Surveys 16:1; Lundberg & Lee (2017) NeurIPS 30:4765
Model Overfitting	Poor cross-regional generalization; models trained in one region fail in others	High	Applied researchers, precision agriculture practitioners	Models trained in temperate regions show R^2 drop of 0.15–0.35 when applied to tropical/arid soils	Transfer learning and domain adaptation partially address this; no universal solution	Transfer learning with domain adaptation; ensemble approaches; global spectral libraries; cross-validation with geographically diverse test sets	De Caires et al. (2025) Discover Soil 2:53; Minasny & McBratney (2025) Eur. J. Soil Sci. 76:e70093; Gholizade et al. (2025) Int. J. Syst. Assur. Eng.
Computational Cost	High computational requirements for DL training; GPU dependency	Medium	Resource-limited institutions, developing country researchers	DL model training costs \$100–\$10,000 per run on cloud GPU; inaccessible for most developing country institutions	Cloud computing partially addresses cost; edge computing emerging	Model compression (pruning, quantization); knowledge distillation; federated learning; open-source cloud computing grants	Taye (2023) Computers 12:91; Arroba et al. (2024) Software: Pract. Exp. 54:2272; Dritsas & Trigka (2025) Remote Sensing 17:550
Sensor Cost & Maintenance	High initial investment and ongoing maintenance for IoT sensor networks	High	Smallholder farmers, developing country agriculture	IoT soil monitoring systems cost \$500–\$50,000 per farm; unaffordable for 80% of global	Low-cost sensor development ongoing; shared infrastructure models emerging	Subsidized sensor programs; shared community sensor networks; low-cost DIY sensor	Liakos et al. (2018) Sensors 18:2674; Mowla et al. (2023) IEEE Access 11:145813

				smallholder farmers		kits; mobile phone-based soil testing	; Mansoor et al. (2025) Front. Plant Sci. 16:1587869
Scalability	Computational scalability for high-resolution national/continental soil mapping	Medium	National soil survey agencies, policymakers	Processing 1 km ² hyperspectral imagery requires 10-100 GB storage and hours of processing time	Cloud computing and distributed processing partially address this	Distributed computing frameworks (Apache Spark); cloud-native geospatial processing; model compression for large-scale deployment	Dritsas & Trigka (2025) Remote Sensing 17:550; Arroba et al. (2024) Software: Pract. Exp. 54:2272
Regulatory Barriers	Carbon credit certification complexity; lack of AI audit standards for soil diagnostics	Medium	Agribusiness, carbon market participants, policymakers	AI-based carbon credit verification rejected by 60-70% of certification bodies due to lack of standards	Some voluntary carbon market standards emerging; no universal framework	Standardized AI audit frameworks for soil carbon; regulatory sandboxes for AI soil diagnostics; international standards development (ISO/FAO)	Guha et al. (2024) Geo. Wash. L. Rev. 92:1473; Atapattu et al. (2024) AI Techniques Smart Agric.:7; Avasthi et al. (2025) Hyperautomation Prec. Agric.:49
Technology Adoption	Farmer skepticism; lack of technical capacity; cultural barriers to AI adoption	Medium	Farmers, agricultural extension services	Only 15-25% of farmers in developing countries have adopted AI-based agricultural tools despite availability	Extension services and training programs exist but insufficient scale	Participatory design of AI tools; farmer-centric interface design; local language support; demonstration farms; capacity building programs	Ansari et al. (2024) Agriculture 4.0:355; Shafik (2024) Comput. Intell. IoT Agric.:193; Avasthi et al. (2025) Hyperautomation Prec. Agric.:49

Table 8. Summary of key challenges limiting AI-powered soil health diagnostics with severity ratings, quantitative impacts, current solution status, and recommended mitigation strategies. H = High; M = Medium; L = Low severity. DNN = Deep Neural Network; CNN = Convolutional Neural Network; XAI =

Explainable AI; IoT = Internet of Things; FAIR = Findable, Accessible, Interoperable, Reusable; GAN = Generative Adversarial Network. Key references: Arrouays et al. (2017) *Advances in Agronomy* 125:93–134; Wadoux et al. (2021) *SOIL* 7:107–122; Hassija et al. (2024) *Cognitive Computation* 16:45–74; Liakos et al. (2018) *Sensors* 18:2674; Mowla et al. (2023) *IEEE Access* 11:145813–145852; Guha et al. (2024) *Geo. Wash. L. Rev.* 92:1473.

Table 9: Future Research Directions and Emerging Opportunities in AI-Driven Soil Health Diagnostics

Reviewer #2 Comment 5: 'The discussion on research gaps and future directions is generic and lacks technical specificity. The paper fails to identify concrete open problems or underexplored areas that could guide future research.'

Research Direction	Specific Open Problem / Underexplored Area	Technical Readiness Level (TRL)	Priority Level	Expected Impact / Outcome	Current Barriers	Original References
Multi-Modal Data Fusion	Uncertainty-aware heterogeneous data fusion: developing models that propagate measurement errors from satellite, UAV, IoT, and spectroscopic sources through multi-modal pipelines; standardized APIs for real-time sensor-satellite integration	TRL 4–5 (Lab validated; not field-deployed)	High	20–30% accuracy improvement over single-modality; comprehensive soil health assessment from single integrated platform	Data alignment across different spatial/temporal resolutions; lack of standardized fusion architectures; computational complexity	Wadoux et al. (2021) <i>SOIL</i> 7:107; Liang et al. (2025) <i>Forests</i> 16:971; Wang et al. (2024) <i>Anal. Chem.</i> 96:8109
Explainable AI for Soil Science	Soil-specific XAI benchmarks evaluating explanation quality against domain expert knowledge; causal inference frameworks distinguishing correlation from	TRL 3–4 (Proof of concept; not soil-specific)	High	Practitioner adoption rates increase 30–50%; regulatory acceptance of AI soil diagnostics; scientifically validated AI explanations	No soil-specific XAI evaluation standards; causal inference computationally expensive; Bayesian DL requires specialized expertise	Novielli et al. (2025) <i>Sci. Rep.</i> 15:12527; Wadoux et al. (2025) <i>Eur. J. Soil Sci.</i> 76:e70080; Rudin et al. (2022) <i>Statist. Surveys</i> 16:1

	causation in soil AI predictions; Bayesian uncertainty quantification in DL models					
Edge Computing for Field AI	Soil-specific model compression (pruning, quantization, knowledge distillation) maintaining accuracy within 5% of full-scale models while reducing computational requirements by 80–90%; self-calibrating sensor systems using AI for drift correction	TRL 5–6 (Technology validated; prototype demonstrated)	High	Real-time field-level soil diagnostics without cloud connectivity; 80–90% reduction in computational cost; autonomous sensor operation	Model compression degrades accuracy for complex soil properties; edge hardware limitations; power management for remote deployment	Arroba et al. (2024) <i>Software: Pract. Exp.</i> 54:2272; Mansoor et al. (2025) <i>Front. Plant Sci.</i> 16:1587869; Ojha et al. (2015) <i>Comput. Electron. Agric.</i> 118:66
Federated Learning for Soil Networks	Privacy-preserving collaborative soil model training across distributed farm networks without sharing raw data; communication-efficient federated protocols for low-bandwidth agricultural IoT networks	TRL 3–4 (Proof of concept; not agricultural)	Medium	Global soil model generalization without data sharing; privacy-compliant cross-farm learning; 15–25% accuracy improvement through collaborative training	Communication overhead in low-bandwidth rural areas; non-IID data distribution across farms; convergence challenges	Pandey et al. (2025) <i>AI IoT-Driven Soil Health</i> ; Mowla et al. (2023) <i>IEEE Access</i> 11:145813; Spanaki et al. (2021) <i>Int. J. Inf. Manag.</i> 59:102350
Automated Spectral Preprocessing	Adaptive automated preprocessing pipelines that select optimal preprocessing sequence	TRL 5 (Technology validated; limited deployment)	High	15–25% accuracy improvement over fixed preprocessing; enables non-expert deployment	No universal preprocessing sequence; soil-type-specific optimization required; limited	Knadel et al. (2023) <i>Appl. Spectrosc. Rev.</i> 58:629; Gozukara et al. (2025) <i>SSSAJ</i> 89:e70028;

	(SG filter, SNV, derivative, PCA/PLSR) based on soil type, moisture content, and target property without manual intervention			of spectroscopic soil diagnostics; reduces analysis time from hours to seconds	labeled training data for meta-learning	Mokere et al. (2025) Crit. Rev. Anal. Chem. 55:1304
Cross-Continental Transfer Learning	Domain adaptation frameworks for transferring soil AI models across continental boundaries (e.g., European models to African soils); meta-learning approaches for rapid adaptation with minimal local data (<50 samples)	TRL 4-5 (Lab validated; limited field testing)	High	Enables AI soil diagnostics in data-poor regions; reduces local data collection cost by 60-80%; addresses global soil data inequality	Large domain shift between continental soil types; limited labeled data in target domains; model architecture mismatch	Gholizade et al. (2025) Int. J. Syst. Assur. Eng.; Padarian et al. (2020) SOIL 6:35; Wadoux et al. (2020) Earth-Sci. Rev. 210:103359
Soil Carbon Sequestration Monitoring	AI-driven soil carbon sequestration monitoring systems with $\pm 5\%$ field-scale accuracy for carbon credit verification; integration of satellite, IoT, and spectroscopic data for continuous SOC change detection	TRL 4-5 (Validated in research; not certified)	High	Enables verified carbon credit markets for soil carbon; supports climate change mitigation; potential \$50-200/tonne CO ₂ market value	$\pm 5\%$ accuracy requirement not yet achieved at field scale; temporal variability of SOC; lack of regulatory standards for AI-based verification	Lal (2020) J. Soil Water Conserv. 75:27A; Minasny et al. (2017) Geoderma 292:59; Novielli et al. (2025) Sci. Rep. 15:12527
Digital Twin for Soil Systems	Process-based digital twin frameworks integrating AI	TRL 3-4 (Concept demonstrated; not soil-specific)	Medium	Long-term soil health trajectory prediction (10-50 years);	Model coupling complexity; computational cost of process-	Zeng et al. (2025) Rev. Geophysics 63:e2024RG000836; Wen et al.

	predictions with mechanistic soil models (CENTURY, RothC) for long-term soil health scenario analysis and management optimization			scenario analysis for climate adaptation; optimization of soil management practices	based models; uncertainty propagation across model interfaces	(2025) Adv. Resources Res. 5:350; Minasny & McBratney (2025) Eur. J. Soil Sci. 76:e70093
Quantum Computing for Soil Optimization	Quantum-classical hybrid algorithms for large-scale soil property optimization problems; quantum machine learning for high-dimensional spectral data analysis	TRL 2-3 (Research phase; not applied to soil)	Low-Medium	Exponential speedup for combinatorial soil management optimization; potential breakthrough in high-dimensional spectral analysis	Current quantum hardware (NISQ era) insufficient for practical soil applications; quantum error rates too high; limited quantum ML algorithms	Biazar et al. (2025) Sustainability 17:2250; Dritsas & Trigka (2025) Remote Sensing 17:550
Synthetic Biology Biosensors	Engineered microbial biosensors with standardized, quantifiable responses to specific soil health indicators (heavy metals, pH, nutrient levels); integration with IoT networks for biological soil monitoring	TRL 2-3 (Laboratory proof of concept)	Medium	Novel in-situ biological soil monitoring; real-time detection of soil contamination; complement to physicochemical sensors	Regulatory approval for environmental release; standardization of biosensor response; stability in diverse soil environments	Pandey et al. (2025) AI IoT-Driven Soil Health; Zeng et al. (2025) Rev. Geophysics 63:e2024RG000836

Table 9. Future research directions with technical readiness levels (TRL), priority levels, expected impacts, and current barriers for AI-driven soil health diagnostics. TRL scale: 1 (basic research) to 9 (proven system). SOC = Soil Organic Carbon; DL = Deep Learning; XAI = Explainable AI; IoT = Internet of Things; IID = Independent and Identically Distributed; NISQ = Noisy Intermediate-Scale Quantum; SG = Savitzky-Golay; SNV = Standard Normal Variate; PCA = Principal Component Analysis; PLSR = Partial Least Squares Regression. Key references: Wadoux et al. (2021) SOIL 7:107-122; Novielli et al. (2025) Scientific Reports 15:12527; Arroba et al. (2024) Software: Practice and Experience 54:2272-2296; Lal (2020) Journal of Soil

and Water Conservation 75:27A-32A; Zeng et al. (2025) Reviews of Geophysics 63:e2024RG000836; Gholizade et al. (2025) International Journal of System Assurance Engineering and Management.