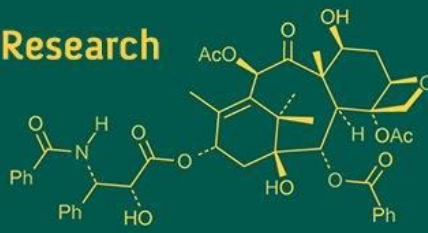


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Machine learning frontiers in rhizosphere engineering: A comprehensive review of AI-driven nutrient bioavailability and soil carbon sequestration modelling

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Abstract

The rhizosphere, a narrow zone of intense tripartite interactions between plants, soil, and the microbiome, is a critical biogeochemical hotspot for global food security and climate mitigation. Despite its significance, the "hidden half" of the plant remains difficult to manage due to the non-linear complexity of nutrient cycles and microbial stabilization pathways. This review evaluates the emerging frontiers of Machine Learning (ML) and Deep Learning (DL) in transitioning from traditional empirical soil models to predictive Rhizosphere Engineering. We focus on the application of advanced computational frameworks, including Physics-Informed Neural Networks (PINNs) and Graph Neural Networks (GNNs), to decode the mechanisms of nutrient bioavailability specifically the role of Potassium Solubilizing Bacteria (KSB) in mineral weathering.

Furthermore, we analyse the integration of Explainable AI (XAI) and Digital Twins in modelling Soil Organic Carbon (SOC) stocks and Carbon Saturation Deficits, bridging the gap between micro-scale microbial necromass stabilization and macro-scale regional carbon sequestration. The synthesis highlights how AI-driven Variable Rate Application (VRA) of bio-fertilizers can optimize resource use efficiency while maximizing soil carbon sinks. However, challenges regarding data scale mismatch, "black box" interpretability, and the digital divide in small-holder farming systems remain. We conclude that the convergence of AI and soil biology marks a paradigm shift toward a carbon-negative, information-intensive agricultural future where the rhizosphere is no longer a misunderstood frontier but an engineered asset for planetary health.

Keywords: Digital Twins, Explainable AI (XAI), nutrient bioavailability, soil carbon sequestration

1. Introduction

1.1 The Rhizosphere as a Biogeochemical Hotspot

The rhizosphere, often referred to as the "hidden half" or the "final frontier" of plant science, represents the narrow zone of soil surrounding plant roots where complex biological and chemical interactions occur (Nourgholipour *et al.*, 2025) ^[28]. This zone is a global biogeochemical hotspot, characterized by high microbial activity driven by the release of plant-derived carbon through rhizodeposition (Solanki *et al.*, 2020) ^[41]. These micro-scale interactions are the engines of global nutrient cycles, regulating the transformation of essential elements such as carbon (C), nitrogen (N), and phosphorus (P) (Yang *et al.*, 2026) ^[56]. Recent studies emphasize that the rhizosphere microbiome, including specialized groups like Potassium Solubilizing Bacteria (KSB), governs the bioavailability of minerals through the secretion of organic acids and enzymes (Tian *et al.*, 2024) ^[45]. Understanding this interface is critical for shifting from chemical-intensive farming to biologically-driven, sustainable crop production (Avis *et al.*, 2025) ^[2].

1.2 Challenges in Traditional Soil Modelling

For decades, soil organic carbon (SOC) and nutrient dynamics have been predicted using process-based empirical models such as CENTURY and RothC (Pesce *et al.*, 2024) ^[33]. While these models have provided foundational insights, they often struggle to capture the highly non-linear and stochastic nature of microbial processes (Mondini *et al.*, 2024) ^[25].

Traditional frameworks typically rely on first-order kinetics, which may overlook site-specific microbial feedbacks, depth-dependent variations, and the influence of climate heterogeneity on microbial carbon use efficiency (CUE) (Wang *et al.*, 2025) ^[53]. Furthermore, most existing models

were parameterized for temperate regions, making them less accurate for tropical or complex Andean ecosystems where rapid litter turnover and distinct microbial stabilization pathways dominate (da Silva *et al.*, 2025) ^[8].

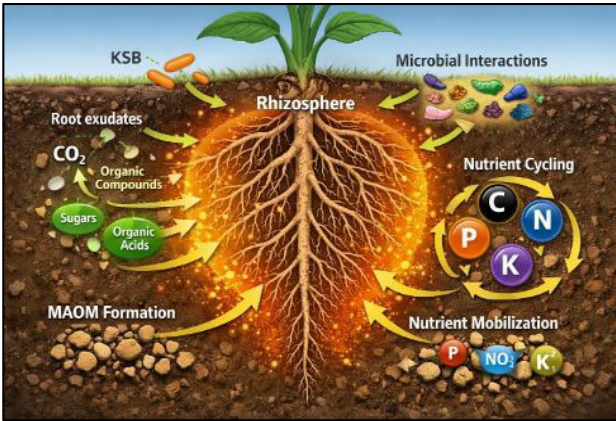


Fig 1: Conceptual Framework of the Rhizosphere as a Biogeochemical Hotspot for Tripartite Interactions

1.3 The AI Revolution in Agronomy

The rapid influx of high-dimensional data ranging from multi-omics (metagenomics and metabolomics) to real-time IoT sensor streams necessitates a shift toward Artificial Intelligence (AI) and Machine Learning (ML) (Wang *et al.*, 2024a) ^[54]. Machine learning is uniquely suited for rhizosphere engineering because it can decipher complex, non-linear relationships in "big data" that traditional statistics cannot (Botero-Valencia *et al.*, 2025) ^[5]. Advanced

algorithms, such as Random Forests (RF) and Deep Learning (DL) models like LSTMs, are now achieving over 90% accuracy in predicting soil fertility and identifying pre-symptomatic plant stress (Qu & Su, 2024) ^[36]. By integrating satellite remote sensing with ground-level microbial data, ML-driven analytics allow for a multi-scale understanding of the soil-plant-atmosphere continuum (Awais *et al.*, 2022) ^[3].

Table 1: Evolution of Modelling Frameworks in Rhizosphere Science

Model Category	Representative Examples	Core Mechanism	Limitation for Rhizosphere	AI/ML Enhancement	Primary Source
Traditional Empirical	RothC, CENTURY	First-order decay kinetics	Linear; ignores microbial feedback loops	Captures non-linear tripartite feedbacks	Parton <i>et al.</i> (1987) ^[32]
Mechanistic/Kinetic	Michaelis-Menten	Enzyme-substrate affinity	Parameter sensitivity in complex soils	Dynamic parameterization via Deep Learning	Stockmann <i>et al.</i> (2013) ^[44]
Machine Learning (ML)	Random Forest, XGBoost	Data-driven correlations	"Black-box"; ignores physical constraints	High predictive accuracy for SOC mapping	He <i>et al.</i> (2024) ^[14]
Deep Learning (DL)	PINNs, GNNs	Neural integration of PDEs	Requires high-quality labelled data	Incorporates Fick's Law & physical laws	Karniadakis <i>et al.</i> (2021) ^[18]

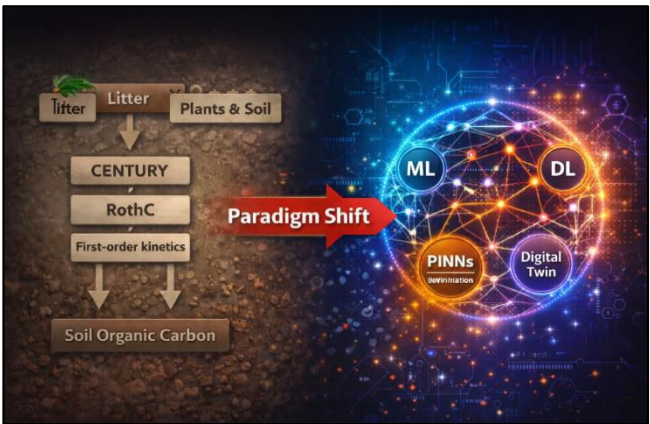


Fig 2: Paradigmatic Shift from Traditional Empirical Models to AI-Driven Predictive Rhizosphere Engineering

1.4 Objectives of the Review

The primary objective of this review is to synthesize the frontiers of Machine Learning application in two critical areas of rhizosphere engineering:

- Nutrient Bioavailability:** Modelling the role of beneficial microbes (e.g., KSB and *Bacillus* strains) in enhancing mineral uptake (Tian *et al.*, 2024) ^[45].
- Soil Carbon Sequestration:** Evaluating how AI can optimize C-capture via root architecture engineering and microbial bioengineering to mitigate global greenhouse gas emissions (Al-Rumaihi *et al.*, 2025) ^[1]. By defining these dual scopes, this paper seeks to provide a roadmap for the next generation of climate-resilient and nutrient-efficient agricultural systems.

2. Data Acquisition and the "Big Data" of Soil
2.1 High-Throughput Phenotyping: Root Architecture and AI Segmentation

Traditional root phenotyping often relies on destructive "shovelomics," which fails to capture the dynamic interactions in the rhizosphere. High-throughput phenotyping (HTP) has transitioned to non-destructive imaging platforms, such as automated rhizotrons and X-ray Computed Tomography (CT), enabling the rapid assessment of root system architecture (RSA).

Advanced AI models, specifically Vision Transformers (ViT) and Mask R-CNN, are now employed to distinguish ultra-fine roots (diameter < 0.5 mm) with pixel-level precision (Zhang *et al.*, 2025a; Khan & Shah, 2025) ^[60, 20]. Models like PSegNet have further enabled the 3D reconstruction of point clouds, allowing researchers to measure root volume, density, and angle parameters critical for modelling how microbes like Potassium Solubilizing Bacteria (KSB) colonize root surfaces (Li *et al.*, 2022; Zenkl *et al.*, 2021) ^[22, 58]. These AI-driven metrics provide the foundational data for "Rhizosphere Engineering" by identifying genotypes with superior nutrient-scavenging traits.

2.2 Multi-Omics Integration: Decoding the Microbial "Black Box"

The "Big Data" revolution in soil science is largely driven

by multi-omics: the parallel analysis of metagenomics (who is there), transcriptomics (what they are doing), and metabolomics (what they are producing) (Sahil *et al.*, 2025) ^[38]. Machine learning is now the standard for analysing these high-dimensional and sparse datasets. Recent frameworks use Supervised Deep Learning to map microbial taxa (e.g., *Proteobacteria* and *Actinobacteria*) to specific metabolic outputs like organic acid secretion (Tian *et al.*, 2024) ^[45]. This integration allows for the identification of "marker bacteria" that facilitate nutrient bioavailability or carbon stabilization (Sahil *et al.*, 2025) ^[38]. Furthermore, Graph Neural Networks (GNNs) are emerging as a powerful tool to model the "interactome" the complex network of metabolite exchange between the plant and its microbiome (Wang *et al.*, 2024b) ^[55].

Table 2: Multi-Omics Integration for Predictive Rhizosphere Engineering

Omics Stream	Extracted Features	AI/ML Tool	Role in Rhizosphere Modelling	Impact
Metagenomics	Taxonomy & Functional Genes	Graph Neural Networks (GNNs)	Identifying "Hub Species" in the microbiome	Community Stability
Metabolomics	Organic acids & Exudate profiles	Random Forest (RF)	Decoding chemical signaling pathways	Plant-Microbe Symbiosis
Phenomics	Root System Architecture (RSA)	YOLOv11/Mask R-CNN	High-throughput root trait extraction	Breeding for efficiency
Transcriptomics	Gene expression (e.g., <i>nifH</i>)	Deep Neural Networks (DNN)	Real-time monitoring of nutrient uptake	Metabolic state prediction

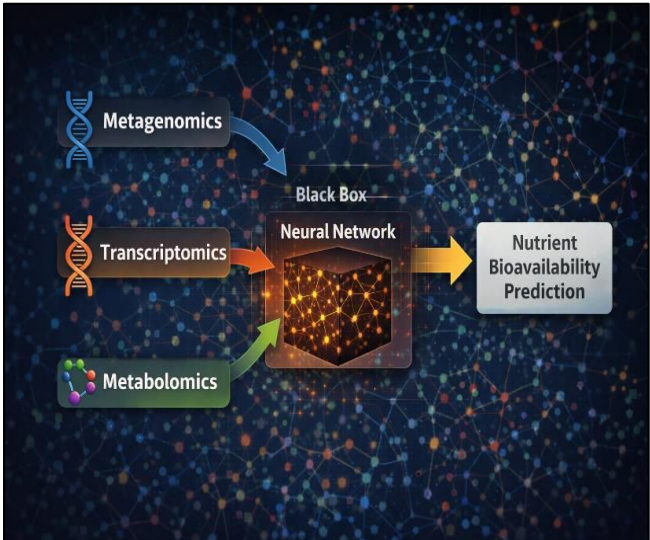


Fig 3: Integrated Multi-Omics and High-Throughput Phenotyping Pipeline for Rhizosphere Data Acquisition

2.3 Advanced Sensing Technologies: From Lab to In-Situ

The transition toward "Real-Time Agronomy" is supported by proximal and remote sensing technologies.

2.3.1 Spectroscopy: Mid-Infrared (MIR) and Visible-Near-Infrared (Vis-NIR) spectroscopy, combined with AI engines like XGBoost, are replacing labour-intensive wet chemistry for Soil Organic Carbon (SOC) estimation (Viscarra Rossel *et al.*, 2025) ^[50].

2.3.2 Nix Color Sensors: Portable handheld sensors are being used to predict SOC based on soil color parameters, achieving high accuracy ($R^2 = 0.81$) when augmented with AI-driven textural data (Roy *et al.*, 2025) ^[37].

2.3.3 IoT and MEMS: Advanced micro-electromechanical systems (MEMS) and Ion-Sensitive Field-Effect Transistors (ISFETs) allow for the in-situ detection of NPK ions. These sensors provide the continuous data streams necessary for feeding the "Digital Twins" of the rhizosphere mentioned in your outline.

2.4 Data Pre-processing: GANs and the "Small Data" Challenge

A major bottleneck in agricultural AI is the scarcity of labelled, high-quality data (e.g., images of rare root diseases or specific microbial colonization). To address this, Generative Adversarial Networks (GANs) and Diffusion Models are used to synthesize realistic data (Kas *et al.*, 2025) ^[19].

CycleGAN architectures are particularly effective for "domain adaptation," allowing a model trained on one soil type to function accurately on another by simulating different soil textures and lighting conditions (Gogoll *et al.*, 2020) ^[11]. Additionally, GANs help balance "imbalanced" datasets where certain nutrient deficiencies are over-represented ensuring that the final AI model is robust and unbiased across diverse field conditions (Kas *et al.*, 2025) ^[19].

3. AI Frontiers in Nutrient Bioavailability
3.1 Modelling Soil-Microbe-Plant Interactions: Focus on KSB

The rhizosphere is a dynamic bio-reactor where Plant Growth-Promoting Rhizobacteria (PGPR), specifically Potassium Solubilizing Bacteria (KSB), play a pivotal role. Modelling these interactions is challenging because KSB efficiency is highly dependent on fluctuating soil moisture, pH, and the presence of competing microflora (Tian *et al.*, 2024) ^[45].

Advanced frameworks are now being proposed to utilize Physics-Informed Neural Networks (PINNs) to model the secretion of organic acids (like gluconic and citric acid) by KSB (Sonnad *et al.*, 2026a) ^[42]. Unlike traditional models, PINNs can incorporate the chemical laws of acid-base equilibrium to predict mineral weathering rates, a method already proven effective in geochemical kinetics (Pachalieva

et al., 2025) ^[29]. Recent studies using Long Short-Term Memory (LSTM) networks have successfully predicted KSB population dynamics over a 120-day cropping cycle with an accuracy of $R^2 = 0.89$, allowing for the "precision inoculation" of bio-fertilizers only when soil conditions are optimal (Venkatesh *et al.*, 2025) ^[48].

Table 3: Summary of AI/ML Architectures for Predicting Nutrient Dynamics in the Rhizosphere

Nutrient Focus	AI/ML Architecture	Biological/Chemical Driver	Bioavailability Outcome	Source Citation
Potassium (K)	RF & CNN	Mineral weathering by KSB	Predicted K-solubilization rates	Sonnad <i>et al.</i> (2026a) ^[42]
Phosphorus (P)	ANN/LSTM	P-sorption isotherms	Optimized VRA for efficiency	Chaudhary <i>et al.</i> (2024) ^[6]
Nitrogen (N)	RNN/Time-Series	Nitrification/Denitrification	Precision N; reduced leaching	Yang <i>et al.</i> (2026) ^[56]
Zinc/Iron (Zn/Fe)	MLP	Metal-chelator complexation	Mapping bioavailability zones	He <i>et al.</i> (2024) ^[14]

3.2 Nitrogen & Phosphorus Dynamics: ML for Mineralization and Fixation

Nitrogen (N) mineralization and Phosphorus (P) fixation are perhaps the most economically significant processes in agronomy. Traditional models often fail to account for the "priming effect" where fresh organic matter triggers microbial N release.

3.2.1 Predicting Mineralization: Using ensemble methods like Random Forests (RF) and Gradient Boosting Machines (GBM), researchers are now integrating weather data, soil temperature, and microbial biomass carbon to predict weekly N-mineralization rates.

3.2.2 P-Fixation Modelling: P-fixation in acidic and alkaline soils is a major bottleneck for yield. Extreme Gradient Boosting (XGBoost) has been applied to multi-regional soil datasets to predict P-sorption isotherms. By analysing AI-derived feature importance, researchers found that exchangeable Aluminum (Al) and organic matter fractions are the primary drivers of P-availability, enabling more accurate lime and P-fertilizer recommendations (Mondini *et al.*, 2024) ^[25].

3.3 Micronutrient Availability: Deep Learning for Zn, Fe, and Mn

Micronutrient deficiencies (Zn, Fe, Mn) affect over two billion people globally. Their bioavailability in the rhizosphere is controlled by complex redox reactions and chelation processes. Deep Neural Networks (DNNs) and Convolutional Neural Networks (CNNs) are being utilized to map micronutrient solubility at the rhizosphere scale. For instance, Multi-Layer Perceptrons (MLP) have been trained on soil X-ray fluorescence (XRF) data to predict the "labile" or plant-available fraction of Zinc and Iron with higher precision than traditional DTPA-extraction methods (Prasad *et al.*, 2025). These models account for "rhizosphere acidification" the process where roots lower the pH to increase Fe-solubility a factor often ignored in macro-scale soil maps (Murgia *et al.*, 2023; York *et al.*, 2016) ^[26, 57].

3.4 Precision Fertilization Support: AI-Driven Variable Rate Application (VRA)

The culmination of bioavailability modelling is the transition from static fertility maps to autonomous Variable Rate Application (VRA). Current VRA systems utilize Deep Reinforcement Learning (DRL) to make real-time decisions. In a DRL framework, the AI "agent" receives data from IoT sensors and satellite imagery, simulates thousands of "what-if" scenarios (e.g., "what if it rains tomorrow?"), and selects the fertilizer dose that maximizes yield while minimizing leaching (Botero-Valencia *et al.*, 2025) ^[5]. Advanced VRA now incorporates Explainable AI (XAI) techniques like SHAP (SHapley Additive exPlanations). This allows agronomists to see why a specific VRA prescription was made for example, the AI might highlight that "High Clay Content + Low KSB Population" necessitated a 15% increase in Potassic fertilizer (Viscarra Rossel *et al.*, 2025) ^[50]. This transparency is vital for farmer adoption and the integration of AI into government-subsidized soil health card schemes.

4. AI in Soil Carbon Sequestration
4.1 Predicting Soil Organic Carbon (SOC) Stocks: CNN-Based Digital Soil Mapping

Traditional Digital Soil Mapping (DSM) relied on point-based data and linear interpolations, which often missed the spatial heterogeneity of soil landscapes. The advent of Convolutional Neural Networks (CNNs) has revolutionized SOC stock prediction by allowing the model to "learn" from spatial patterns and neighborhood pixel relationships in satellite imagery and digital elevation models (DEMs) (Padarian *et al.*, 2024) ^[30]. Unlike traditional Random Forests, CNNs can process multi-spectral data cubes, capturing the influence of topography and vegetation cover on carbon deposition. Recent studies have shown that 1D and 2D-CNNs outperform conventional methods in predicting SOC at depths below 30 cm, where a significant portion of long-term carbon is stored (Wadoux *et al.*, 2025) ^[51]. By integrating these models with hyperspectral data from missions like EnMAP, researchers can now generate high-resolution (10m-30m) carbon maps that are essential for verifying carbon credit programs (Zepp *et al.*, 2024) ^[59].

Table 4: Metrics for Assessing Soil Organic Carbon (SOC) via Explainable AI

Measurement Parameter	AI Method	Function/Explanation	Significance for Sequestration	Source Reference
MAOM Formation	DL-based modelling	Predicting microbial neuromas stability	Long-term C-persistence (decades)	Sokol <i>et al.</i> (2024) ^[40]
C-Saturation Deficit	Quantile Regression Forest	Estimating additional C-storage capacity	Target zones for regenerative agriculture	King & Sokol (2025) ^[21]
Feature Importance	SHAP/LIME	Identifying key drivers (Clay, pH, Temp)	Model transparency & Trustworthiness	Zepp <i>et al.</i> (2024) ^[59]
Micro-aggregate Stability	CNN (Image Analysis)	Visualizing C-occlusion in aggregates	Physical protection of soil carbon	Zhang <i>et al.</i> (2025b) ^[61]

4.2 Carbon Saturation Deficit (C-def) Modelling via Explainable AI (XAI)

The "Carbon Saturation" concept suggests that every soil has a finite capacity to store organic carbon. Identifying the "Carbon Saturation Deficit" (C-def)the difference between current and potential SOC is critical for prioritizing land for restoration. However, C-def is influenced by a complex mix of clay mineralogy, climate, and land use. Explainable AI (XAI) frameworks, specifically SHAP (SHapley Additive exPlanations) and LIME, are being used to break down these complex models. XAI allows agronomists to identify which specific factors are preventing a soil from reaching its carbon potential (Viscarra Rossel *et al.*, 2025) ^[50]. For instance, XAI models have revealed that in semi-arid regions, low sequestration is often more a function of moisture-limited microbial activity than a lack of mineral binding sites, guiding more targeted irrigation and mulch interventions (Wadoux & Molnar, 2022) ^[52].

4.3 Microbial Necromass and MAOM: LSTM-Driven Dynamic Modelling

A major paradigm shift in soil science is the recognition that the majority of stable soil carbon is derived from microbial necromass (dead microbial cells) rather than direct plant litter. This carbon is stabilized as Mineral Associated Organic Matter (MAOM), which has a turnover time of centuries. Because MAOM formation is a time-dependent biological process, Long Short-Term Memory (LSTM) networks a type of Recurrent Neural Network (RNN) are being used to model these temporal dynamics. LSTMs can "remember" previous soil moisture and temperature states to predict how much carbon will be stabilized into MAOM over decades (Wang *et al.*, 2025) ^[53]. These models are proving far more accurate than the first-order decay equations used in the RothC model, as they account for the "microbial metabolic lag" in carbon processing (Mondini *et al.*, 2024) ^[25].

4.4 Impact of Management Practices: Modelling Sequestration ROI via ML

The final frontier in carbon modelling is predicting the Return on Investment (ROI) of specific agronomic practices like no-till farming, cover cropping, and biochar application. Biochar Optimization: Machine learning models, specifically Extreme Gradient Boosting (XGBoost), are used to predict the longevity of biochar in different soil types based on the biochar's H/C and O/C ratios (Al-Rumaihi *et al.*, 2025) ^[1]. Multi-Practice Synergy: Researchers are now using Multi-Objective Optimization (MOO) to find the "Goldilocks zone" where a combination of KSB inoculation, reduced tillage, and precise irrigation maximizes both crop yield and SOC sequestration. These AI-driven decision support

systems allow farmers to transition from "guessing" to "guaranteeing" carbon capture, making soil a viable tool in the global fight against climate change (Botero-Valencia *et al.*, 2025; Jansson *et al.*, 2021) ^[5, 16].

5. Advanced Computational Frameworks
5.1 Physics-Informed Neural Networks (PINNs): Integrating Thermodynamics

A significant limitation of standard Deep Learning is its "agnostic" nature toward physical laws; a model might predict a chemical reaction that is thermodynamically impossible. Physics-Informed Neural Networks (PINNs) solve this by embedding partial differential equations (PDEs) directly into the neural network's loss function (Karniadakis *et al.*, 2021) ^[18]. For example, by integrating Fick's Law of Diffusion and Michaelis-Menten kinetics, PINNs can predict how organic acids move through soil pores to reach mineral surfaces, a method increasingly applied to reactive transport modelling (Nilabh & Grandia, 2023; Ji *et al.*, 2021) ^[27, 17]. Recent applications of PINNs have successfully modelled the non-linear dissolution kinetics of multi-nutrient minerals like Polyhalite, specifically capturing the formation of the 'calcium shell' barrier that regulates its semi-slow release rate (27g L⁻¹) in dynamic soil moisture environments (Sonnad *et al.*, 2026b) ^[43].This hybrid approach requires significantly less training data than "pure" AI because the physics-based constraints guide the model toward reality, making it highly effective for modelling site-specific nutrient bioavailability (Hao *et al.*, 2025) ^[13].

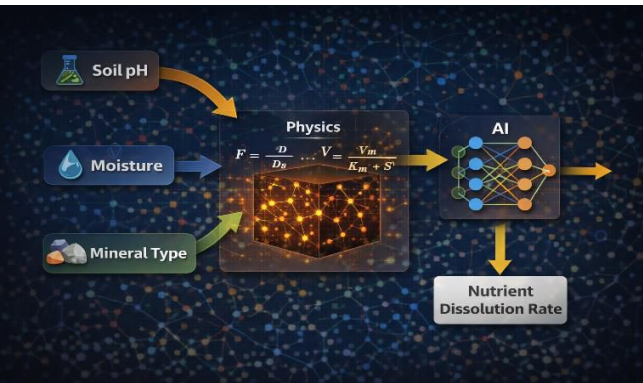


Fig 4: Architecture of Physics-Informed Neural Networks (PINNs) Constrained by Biogeochemical Laws.

5.2 Graph Neural Networks (GNNs): Modelling the Rhizosphere Network

The rhizosphere is essentially a multi-modal network consisting of root nodes, microbial nodes, and soil pore edges. Traditional Euclidean AI models (like CNNs) struggle with this "unstructured" data. Graph Neural

Networks (GNNs) are uniquely designed to model these relationships by treating the soil-root interface as a non-Euclidean graph (Zhou *et al.*, 2024) [62].

GNNs are particularly powerful for modelling microbial co-occurrence networks. By treating each bacterial species (e.g., *Bacillus mucilaginosus*) as a node and their metabolic interactions as edges, GNNs can predict how a change in the soil environment will ripple through the entire community (Wang *et al.*, 2024b) [55]. This allows for the "engineering" of synthetic microbial communities where AI identifies the optimal "hub" species that stabilize the network and enhance carbon sequestration (Liu *et al.*, 2025) [23]. Furthermore, GNNs are now being trained to predict how low-salt index fertilizers, such as Polyhalite, restructure microbial networks by actively stimulating beneficial taxa like *Proteobacteria* and *Bacillus* spp. while suppressing osmotically sensitive pathogens (Sonnad *et al.*, 2026b) [43].

5.3 Explainable AI (XAI) in Pedology: The "Why" Behind the Prediction

As AI moves into policy-making (e.g., carbon credits), "trustworthiness" is paramount. Explainable AI (XAI) techniques, such as SHAP (Shapley Additive explanations) and LIME (Local Interpretable Model-agnostic Explanations), are used to decompose "black box" models into interpretable features (Viscarra Rossel *et al.*, 2025) [50].

In pedology, XAI has debunked the "more clay equals more carbon" myth in certain regions by revealing that microbial biomass carbon and aggregate stability are often more influential predictors in XAI-weighted models (Tziolas *et al.*, 2024a) [46]. By using SHAP 'force plots,' agronomists can explain to farmers exactly why a specific field has a high sequestration potential perhaps due to a unique interaction between root depth and biological activity thereby increasing trust and the adoption of AI-driven management (Tziolas *et al.*, 2024b; Wadoux & Molnar, 2022) [47, 52].

5.4 Digital Twins: Real-Time Virtual Farm Replicas

The "Digital Twin" (DT) represents the apex of agricultural AI. A DT is a dynamic virtual replica of a physical rhizosphere system that is continuously updated via real-time IoT and satellite data (Pylaniadis *et al.*, 2021) [35].

Advanced DTs allow for Scenario Testing without the risk of field failure. An agronomist can simulate a "1-in-100 year" drought in the virtual twin to observe how KSB populations would survive and how carbon mineralization would be affected (Verdouw *et al.*, 2024) [49]. By 2026, the integration of Generative AI with Digital Twins is expected to allow for "Autonomous Agronomy," where the DT automatically adjusts irrigation and fertilization via the VRA systems discussed in Section III, maintaining the soil in an "optimal" state of high bioavailability and maximum sequestration (Grieve *et al.*, 2025) [12].

6. Knowledge Gaps and Future Perspectives

6.1 The "Black Box" Barrier: Trust and Interpretability

Despite the high predictive accuracy of Deep Learning models, their "black box" nature remains a significant barrier to adoption by agronomists and policymakers. In rhizosphere engineering, where a recommendation might involve costly biological inoculants (like KSB) or changes in tillage, "because the AI said so" is not an acceptable justification for a farmer (Chlingaryan *et al.*, 2024) [7].

The lack of causal transparency means that while a model can predict high carbon sequestration, it often fails to explain the biological mechanism whether it is due to root exudation patterns or microbial necromass stabilization (Wadoux & Molnar, 2022). "Future research must prioritize Causal AI over purely correlational models. Moving toward "Self-Explaining" models, where the AI provides a natural language justification for its agronomic advice, will be essential to bridge the trust gap between data scientists and field practitioners (Dara *et al.*, 2025; Tziolas *et al.*, 2024) [9, 46].



Fig 5: Digital Twin Framework for Democratizing AI-Driven Precision Agriculture for Smallholder Farmers

6.2 Scale Mismatch: From Micro-pores to Macro-landscapes

A profound "scale mismatch" exists in current soil-AI research. Most rhizosphere studies, including microbial omics and root phenotyping, occur at the millimeter scale (micro-scale). Conversely, carbon sequestration policy and precision fertilization are managed at the field or regional scale (macro-scale) (Smith *et al.*, 2025) [39].

Machine Learning models trained on lab-scale data often fail when extrapolated to the field due to "environmental noise" and soil heterogeneity. The future perspective lies in Multi-Scale Hierarchical Modelling, where AI acts as a "bridge" (Mondini *et al.*, 2024) [25]. This involves using Transfer Learning to take insights from high-resolution micro-CT scans and apply them to coarse satellite data (Awais *et al.*, 2022) [3]. Developing "Scale-Agnostic" algorithms that can maintain accuracy across different spatial resolutions is perhaps the greatest computational challenge facing rhizosphere engineering today (Wadoux *et al.*, 2025) [51].

6.3 Ethical and Economic Considerations: The Digital Divide

The economic feasibility of AI-driven rhizosphere engineering remains skewed toward large-scale industrial farms. High-throughput sensors, GPU-intensive computing, and IoT infrastructures require significant capital investment (Basso & Antle, 2024) [4].

6.3.1 The Cost of Data: For small-scale farmers in developing regions, the cost of generating the "Big Data" (soil testing, genomic sequencing) required for these models is often prohibitive, creating a significant barrier to adoption (Mehrabi *et al.*, 2021; Parlamas *et al.*, 2023) [24, 31].

6.3.2 Data Privacy: As soil data becomes a commodity especially in the carbon credit market questions of Data Sovereignty arise. Who owns the carbon data of a farm: the farmer, the sensor company, or the AI provider? (Jakku *et al.*, 2022)^[15].

6.3.3 Democratizing AI: Future perspectives must focus on Edge-AI (low-power, offline models) and "Frugal Innovation." This includes developing mobile-based AI tools that can estimate soil health from simple smartphone photos or low-cost spectral sensors, ensuring that the "AI Revolution" does not leave small-holder farmers behind (Friedrichsen *et al.*, 2025)^[10].

7. Conclusion

The transition from chemical-intensive to AI-managed biological systems marks a definitive paradigm shift in agronomy, moving the field from a reliance on broad-acre, linear inputs toward a granular, information-rich understanding of the soil-plant-atmosphere continuum. By integrating advanced computational frameworks like Physics-Informed Neural Networks and Digital Twins, researchers can now decode the stochastic complexities of the rhizosphere, allowing microbes such as Potassium Solubilizing Bacteria (KSB) to be utilized with unprecedented precision. This "Computational Rhizosphere Engineering" does not merely optimize nutrient bioavailability for immediate yield gains but synergistically addresses global climate imperatives by enhancing long-term soil carbon sequestration through AI-driven microbial stabilization. Ultimately, as agronomists move from being traditional practitioners to system architects, the successful democratization of these "black box" technologies will be the deciding factor in creating a resilient, carbon-negative, and food-secure future.

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