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Hybrid AI Models for Predictive and Prescriptive Soil Analytics

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Abstract

Increasing incorporation of artificial intelligence (AI) within soil science has resulted in the origin new frontiers on both predictive and prescriptive basis, including management scheduling optimization, soil property forecasting and site-specific recommendations. Hybrid artificial intelligence (HAI) models combine the spatial feature extraction feature of solitary models with the temporal modelling attributes of large-spectrum models. HAI models provide active decision support, recommending fertilizer rates, irrigation schedules and land management practices calibrated to site-specific, climate and crop conditions. Bibliographic analysis of published literature from the past decade reveals a rapidly globalizing research landscape. With higher adaptation rate of AI-based technologies, HAI technologies have shifted from a niche sector to globally embraced, multi-dimensional research enterprise. The convergence of hybrid architectures, explainable modelling frameworks and expanding international collaborations signals that digital soil systems are no longer a theoretical concept but an emerging operational reality.

Keywords: Deep learning, Machine learning, Predictive soil management, Prescriptive soil management

Introduction

Tools pertaining to soil assessment still rely on laboratory analysis that require relatively longer time periods to return results and soil sampling protocols being followed to date still miss large heterogeneity. Further, rapid urbanization, population growth and climate change are necessitating changes in conventional food production frameworks to allow sustained crop production. New soil management issues are arising that require critical evaluation and targeted amelioration to ensure food security paradigms at a global stage. The result is a dangerous mismatch: our soils are changing faster than our ability to identify, interpret and act on those changes. This is precisely the gap that hybrid AI (HAI) models are beginning to close. Unlike conventional approaches, which rely entirely on data-driven pattern recognition or on rigid physical process equations, HAI models integrate core tenets of established models to extract maximum computational efficiency and result optimization. While statistical tools serve descriptive and inferential purposes, artificial intelligence (AI) tools can be used for forecasting of soil water content from diverse inputs, optimizing irrigation schedules towards defined soil health goals and recommending best management practices tailored to specific field conditions. This article explores how HAI models are transforming soil analytics from a retrospective diagnostic exercise into a forward-looking decision engine that is capable of guiding farmers, agronomists and policymakers toward healthier soils and more resilient food systems.

Data Collection and Methodology

A systematic bibliographic dataset of 14,839 records was assembled from the Scopus database using three keyword combinations: 'Artificial intelligence', 'Soil science' and 'Hybrid AI models'. Two complementary analytical techniques were applied: temporal network analysis and Sankey flow analysis.

Temporal Network Analysis

The temporal network analysis reveals the evolution of international research collaboration in AI-soil science from

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2019 to 2024 (Figure 1). China and the United States emerge as the dominant research hubs, with the largest node sizes reflecting their disproportionate publication volumes. India, Iran, South Korea, Malaysia and several European nations (Germany, Italy, Spain, France, UK) constitute a second tier of active collaborators. Recent years (2023-2024) are characterised by a proliferation of new bilateral collaborations, particularly between Asian and Middle Eastern institutions, suggesting a geographical broadening of the research community. Notably, collaboration links from 2019-2021 predominantly connect established research centres in North America, Western Europe and East Asia. Post-2022 links show expanding engagement from countries including Vietnam, Ethiopia, Nigeria, Bangladesh, Jordan and Saudi Arabia, nations where soil degradation challenges are pressing but research capacity remains limited. This suggests an emerging South-South and North-South knowledge transfer dynamic.

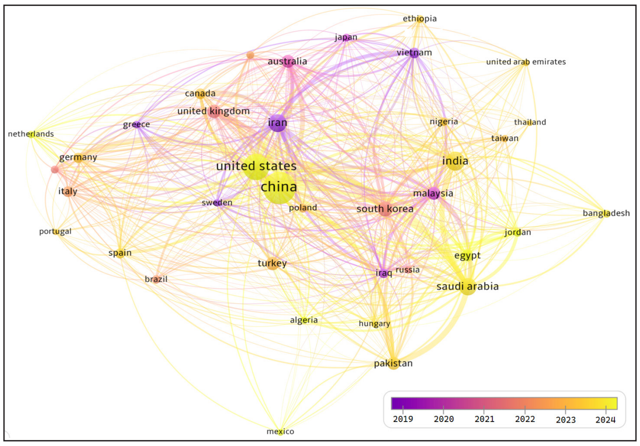

Figure 1: Temporal network analysis pathway map

Sankey Flow Analysis

China is the largest contributor by publication volume, followed by the USA and India (Figure 2). The high-citation class flow is dominated by papers published in IEEE, The Science of the Total Environment, Environmental Research and Journal of Environmental Management indicating that the most impactful AI-soil research appears in environmental science and engineering journals rather than dedicated soil science outlets. Publication volumes peak around 2023-2024, with a notable surge of highly cited work appearing from 2019-2021, consistent with the maturation of deep learning (DL) applications and the growing availability of remote sensing data products for soil mapping. The predominantly

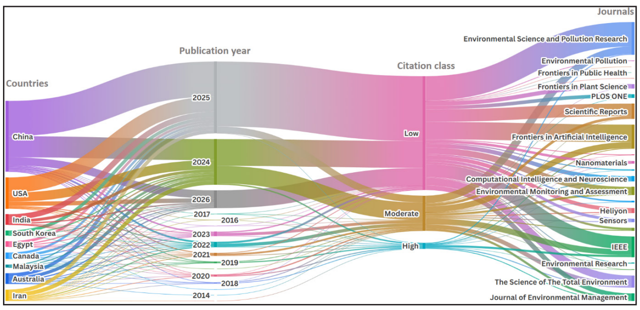

Figure 2: Sankey analysis multi-step alluvial diagram

'low citation' classification of 2025 publications reflects their relatively newer origin rather than low impact.

Predictive Soil Analytics

Estimating soil properties such as organic carbon stocks, nutrient profiles, moisture content and pH demand costly laboratory analysis in addition to slow and spatially limited sampling campaigns. In a comprehensive review of soil organic carbon (SOC) prediction technologies, Ding *et al.* (2025) confirmed that simulated output (biogeochemical model sourced) incorporation as supplemental training data for AI allows causal relationships in SOC turnover to be embedded into empirical modelling while maintaining predictive accuracy. Evidence also suggests that DL models often outperform classical Machine learning (ML), though no best algorithm exists. At the field scale, Zhang *et al.* (2024) developed a hybrid framework coupling the RothC process-based model with Random forest for SOC prediction in eastern China. The hybrid model achieved the best performance with 19% improvement in root mean square error (RMSE) against the standalone ML model. For soil nutrient prediction specifically, Kammerlander *et al.* (2025) exhibited that HAI models such as Random Forests, XGBoost and Fully Connected Neural Networks, trained on LUCAS soil datasets and Sentinel-2 satellite imagery achieved robust performance in soil N, P, K and pH prediction at the continental scale. Hybrid modelling approaches align with explainable AI by integrating known physical mechanisms which ensures predictions are accurate and predictable.

Prescriptive Soil Analytics

Hybrid models can be employed to layout an actionable protocol in order to achieve a specific result, *i.e.*, optimal soil moisture level, crop yield, nutrient supplementation, *etc*. Real-time data collection coupled with inferential models that can assess and simulate future steps to drive plant nutrition adapted to the changes in exogenous factors allows for enhanced resource use efficiency and output augmentation. Venkateswara and Padmanaban (2025) developed a TabNet-based DL system for fertilizer recommendation that builds upon attention-driven learning on IoT-enabled soil and climate data. Further, to enhance transparency, SHAP was applied at the final stage to provide post-hoc interpretability, providing insights to the model's rationale leading to a specific recommendation. The model achieved a classification accuracy of 95.24% and 96.21% for crop recommendation on the Western Maharashtra dataset. At a broader scale, a synthesis of 95 studies by Ugwu *et al.* (2025) reported that AI-mediated precision fertilization involving soil nutrient profile and crop demand prediction at multiple developmental stages, reduces total fertilizer requirement by 28%. Overall, an increase in yield (25%) and water use efficiency (22%) was reported with AI adoption across crop management.

Conclusion

HAI models integrating the mechanistic rigour of process-based science with the pattern recognition power of ML models deliver a powerful tool for high efficiency computation. For prediction, HAI models deliver physically plausible, spatially rich forecasts of soil carbon, nutrient and moisture that no standalone model can match. Further, on prescription-basis they translate forecasts into site specific, explainable management recommendations that are targeted towards achieving higher yield, fertilizer use reduction and lower environmental impact. The bibliographic analysis further confirms the field's rapid expansion and maturation. The road ahead requires harmonized global soil datasets, real-time sensor integration and sustainability constraints embedded within model architectures. When these conditions are met, hybrid AI will form the operational backbone of a genuinely regenerative, data-driven agriculture.

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