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Enhancing soil science research with multi-agent artificial intelligence systems

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Abstract

Soil science is entering a new era characterized by the integration of artificial intelligence (AI) multi-agent systems, extending the field beyond traditional machine learning (ML) applications such as digital soil mapping and spectroscopy. While current ML tools are effective for specific tasks, they often lack the reasoning, contextual integration, and adaptability required to address complex, dynamic soil systems. We propose multi-agent AI systems—autonomous, interactive software agents capable of perceptual processing, planning, and scientific reasoning—as a novel framework to support and accelerate soil science research. These agents can fulfill diverse roles, including synthesizing data from field sensors and remote sensing to create dynamic digital soil twins, generating hypotheses, designing experiments, and simulating climate-driven changes in soil function. To illustrate this approach, we tasked a multi-agent system with creating research hypotheses on the topic of mineral-associated organic carbon saturation in soils. The agents generated five hypotheses on effective versus theoretical saturation thresholds, biological and chemical controls, climate influence, interdisciplinary feedback, and actionable management strategies. Each hypothesis was evaluated for empirical grounding, conceptual breadth, and scientific rigor by experts and a simulated peer review. Our findings highlight the potential of multi-agent AI systems, guided by human experts, to accelerate early-stage discovery, support interdisciplinary exploration, and emulate the scientific review process. Nonetheless, challenges remain, particularly around data quality, model transparency, epistemic overtrust, computational cost, ethical implications, and the retention of foundational scientific knowledge. We emphasize AI as an augmentative partner, not a replacement, for human-led discovery.

KEYWORDS

carbon saturation, climate change, human–AI collaboration, hypothesis generation, multi-agent systems, soil health, soil science, soil security

Key points

- Artificial intelligence (AI) multi-agent systems are poised to revolutionize soil science by enabling autonomous hypothesis generation, experimentation, and analysis of complex datasets.
- Unlike traditional machine learning, these intelligent systems mimic scientific collaboration and combine reasoning, planning, and interdisciplinary insight to support human researchers.
- Applications range from digital soil twins and microbiome monitoring to climate adaptation modeling, promising major advances in sustainable land use and soil carbon management.
- Despite their potential, AI agents face challenges around data quality, interpretability, creativity, and the risk of bias without human oversight and domain expertise.
- Used responsibly, AI can accelerate science, freeing time for deeper understanding while maintaining scientific rigor and environmental accountability.

Introduction

In recent years, soil scientists have rapidly transitioned from machine learning (ML) to broader artificial intelligence (AI) applications to address various disciplinary challenges (1). ML, a subset of AI, focuses on pattern recognition and predictive modeling from data, but AI encompasses more advanced capabilities such as reasoning, autonomous decision-making, and the integration of diverse data sources through generative models such as large language models (LLMs) and multi-agent systems. AI and ML have become increasingly important in tackling global soil security challenges (1–3).

ML continues to play a central role in spatializing and monitoring soil conditions using proximal and remote sensing data, generating digital soil maps at scales ranging from field plots to global landscapes (4, 5). These tools support precision agriculture and inform decisions related to nutrient management and soil carbon stock assessment.

The transition to AI has introduced new capabilities that go beyond mapping. AI systems, especially those incorporating generative capability such as LLMs, can now autonomously synthesize scientific literature. However, most current ML and AI applications in soil science are limited to pattern recognition or prediction based on existing soil data (1, 6). As powerful as these tools are, they typically focus on specific tasks and lack the flexibility and reasoning capacity required to fully address the complexity of soil systems. The next leap forward lies in intelligent automation: the development of multi-agent AI systems that not only process and predict but also have the technical abilities to emulate perception, reasoning, planning, and collaboration. These systems have the potential to work alongside human experts, navigating complex scientific questions, integrating diverse data sources, generating hypotheses, and designing adaptive experiments.

Embracing this paradigm would allow soil science to harness AI's full potential—not to replace researchers but to empower them in addressing the global challenges of soil security, climate resilience, and sustainable land use.

Currently, AI systems generally lack the integration, adaptability, and reasoning capabilities necessary to address the multifaceted and interconnected nature of soil systems. Thus, it remains an unexplored area, partly due to the lack of enabling tools. However, inspired by rapid advancements in other scientific domains, such as biomedicine and materials science (7–10), we propose a perspective shift toward a new paradigm: the use of multi-agent AI in soil science (5).

An AI agent is a software system that uses AI to interact with its information environment, gather information, and perform tasks to achieve specific goals. A multi-agent system consists of multiple AI agents working independently, collaboratively, or autonomously to address a complex problem (11). In such systems, AI is able to make independent decisions and generate novel ideas (12).

We envision multi-agent AI systems not merely as predictive models or data processors but as integrated, intelligent systems capable of perception, reasoning, planning, learning, and collaboration. These agents could coordinate diverse tools, from proximal sensors and satellite imagery to laboratory instruments and complex simulation models, to break down complex soil science problems into manageable and actionable steps. This approach strengthens research design and interpretation before engaging with real-world soil conditions, facilitating the scaling up of ideas or findings.

This paper explores these ideas by examining the potential of multi-agent AI systems in soil science. Specifically, we address the following aims:

- to explain and test a multi-agent AI framework that emulates collaborative scientific reasoning by integrating specialized agents for literature analysis, hypothesis generation, peer review, and experimental design;
- to explore the potential application of multi-agent AI systems in soil science;
- to demonstrate the capability of AI agents to accelerate early-stage soil scientific discovery through structured problem decomposition, interdisciplinary reasoning, and iterative evaluation cycles;
- to evaluate the scientific plausibility, novelty, feasibility, and scalability of AI-generated hypotheses for a specific soil science problem using multi-agent peer review and human-in-the-loop feedback.

AI in soil science: advances and limitations

Recent soil science advances have produced numerous data sources, analytical tools, and models that can be enhanced by ML and AI algorithms (Figure 1), including:

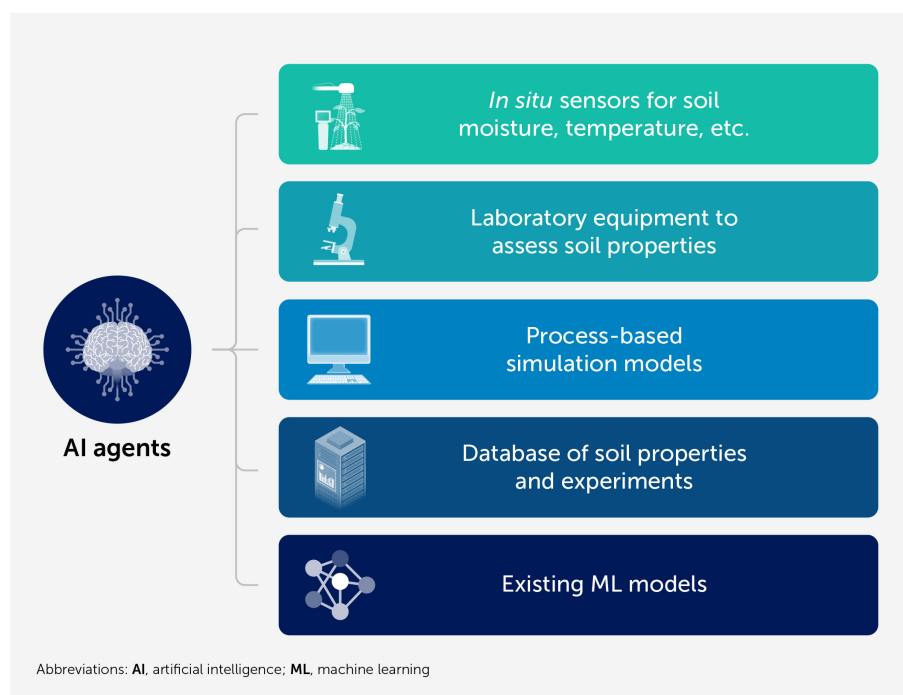


FIGURE 1

Overview of recent advancements in soil science data sources and analytical tools that can be enhanced by machine learning and artificial intelligence algorithms.

- networks of *in-situ* sensors measuring soil moisture, temperature, and physical and chemical properties (13–15);
- sophisticated laboratory equipment for analyzing particle-size distribution, mineralogy, chemical and biological properties, and various spectroscopic methodologies from radio to gamma waves (potentially automatable) (16–18);
- process-based simulation models [e.g., for water, solute, heat and gas transport, organic matter (OM) dynamics, nutrient transport, and crop growth] (19, 20);
- existing ML models for specific predictive tasks, such as pedotransfer functions, soil spectra functions, and spatial prediction models (21–23);
- remote sensing platforms providing data on land cover, topography, relief parameters, and spectral properties (24–27);
- extensive databases of soil properties and experimental results (28, 29).

Despite these successes, current AI applications in soil science are largely task-specific and are developed and applied in isolation (30, 31). These tools typically operate with limited autonomy, requiring substantial human input for data preparation, model training, and interpretation. The reasoning capabilities of many ML and AI models are often embedded implicitly in their architecture rather than explicitly articulated. As a result, many applications are typically geared toward execution, such as in soil spectroscopy, where the focus is on achieving specific predictive objectives. However, they often bypass the traditional scientific process of hypothesis formulation and experimental design (32).

For example, a model may accurately link a spectral response to a soil property, but it will rarely address *why* this relationship exists. As a result, there is a growing concern that much of the ML-based soil science literature lacks robust investigation of the underlying cause-and-effect mechanisms (33). We argue that this gap highlights the need for research that integrates mechanistic understanding with data-driven methods, ensuring that AI not only predicts but also contributes to scientific explanation.

LLMs are currently used to enhance scientific writing and knowledge retrieval. While they demonstrate promising capabilities for conversational interaction, ensuring their reliability and depth of understanding in specialized soil science domains still requires significant human validation and expertise. For example, Khanifar (34) assessed the performance of LLMs in answering soil science-related questions and found that, on average, they could correctly answer only up to 65% of questions from advanced soil science examinations.

This existing foundation, with its strengths and weaknesses, sets the stage for the development of next-generation AI agents capable of more integrated, autonomous, and collaborative scientific exploration and management in soil science. The vision of AI agents transforming scientific discovery is gaining momentum in fields such as chemistry, materials science, and biomedicine, where complex systems, vast datasets, and multidisciplinary knowledge must be integrated (5, 35, 36).

The concept of an “AI scientist” or “co-scientist”—an AI system capable of skeptical learning, reasoning, and collaboration—has been proposed as a framework for generating novel scientific hypotheses aligned with researcher objectives (8, 37, 38). Rather than fully

automating discovery, these agents are envisioned as partners that combine human creativity and domain expertise with AI's capacity for multi-scale data analysis, hypothesis exploration, and task execution.

Central to the AI agent concept is the ability to break down complex problems (39). Soil systems are notoriously complex, involving coupled hydrological, biogeochemical, and physical processes operating across multiple spatial and temporal scales (40). An AI agent could break down a grand challenge, such as predicting the impact of climate change on global soil carbon

storage, into manageable subtasks (Figure 2): i) analyzing regional climate projections, ii) modeling soil moisture dynamics, iii) simulating microbial decomposition rates under different temperature regimes or soil mineralogical domains, iv) integrating remote sensing data on vegetation cover, and v) assessing the effects of various land management practices on subsoil rooting and carbon storage at depth. Each subtask could potentially be handled by specialized modules or even distinct agents within a larger multi-agent system.

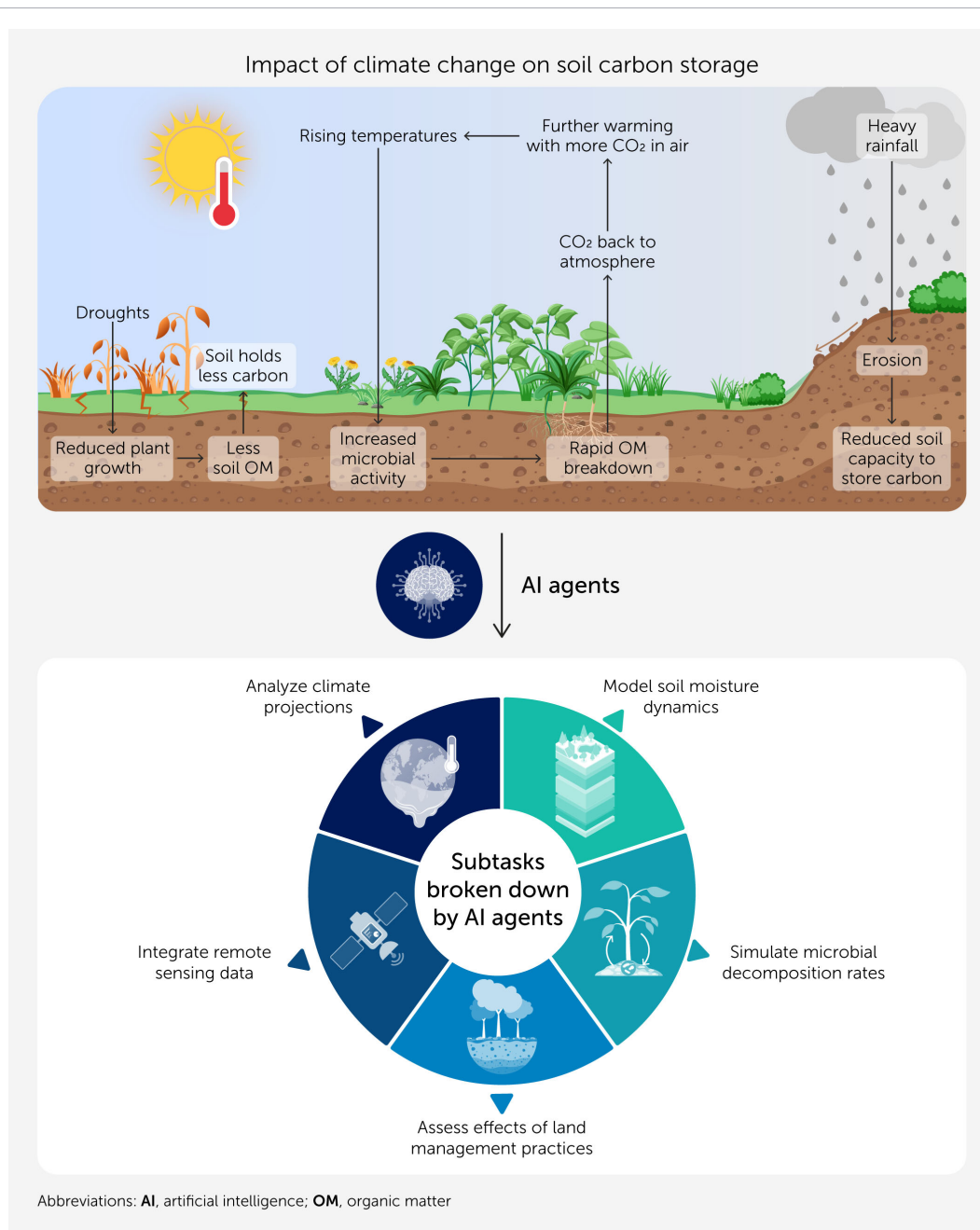


FIGURE 2

An Artificial Intelligence (AI) agent can decompose a grand challenge—such as predicting the impact of climate change on global soil carbon storage—into a series of manageable subtasks. Each subtask can be addressed by specialized modules or distinct agents within a larger multi-agent AI system.

Multi-agent AI systems

Effective problem break down relies on the agent’s ability to integrate and coordinate a diverse array of tools. A multi-agent system can act as an orchestrator, selecting, configuring, and executing these tools within a coordinated workflow, moving beyond the current fragmented use of individual technologies. The agents possess perceived reasoning and planning capabilities that extend well beyond simple data processing (7).

In recent years, the use of multi-agent AI systems has emerged as a transformative approach in scientific research, particularly in fields grappling with vast, complex datasets and interdisciplinary challenges, such as in biomedicine (9, 10). Unlike single-agent models, which are often constrained by limited capabilities, multi-agent frameworks distribute tasks across specialized agents, each equipped with domain-specific knowledge, reasoning strategies, and tools. These systems emulate collaborative scientific workflows involving brainstorming, critique, consensus-building, and iterative refinement. As a result, multi-agent AI systems can accelerate discovery and enhance research quality (5).

Several multi-agent models have been proposed for use in scientific discovery, and Table 1 summarizes key design features, agent roles, and contributions to automated and augmented scientific inquiry across various disciplines.

These models share several core principles:

- *task decomposition*. The system segments a complex research problem into manageable subtasks for specialized agents.
- *collaboration among agents*. Decomposed tasks are delegated to agents with different areas of expertise, promoting collaborative problem-solving akin to human teams.
- *iterative reasoning and refinement*. The system supports cyclical processes of hypothesis generation and evaluation, utilizing feedback from internal and external sources.
- *autonomy with human optionality*. The model can operate autonomously but also allows for human-in-the-loop interactions (e.g., co-pilot mode or human review stages).
- *tool integration*. Agents interface with external tools, databases, and libraries to perform domain-specific tasks.

Here, we propose a multi-agent system for hypothesis generation and experiment design that integrates key components from leading multi-agent AI models (Figure 3). The system begins with a *Planner Agent*, which breaks down the research problem and delegates data segments to specialized supporting agents. These include a *Literature Review Agent* for retrieving relevant prior work, a *Data Analyst Agent* for exploratory data analysis, and a *Tool/Database Agent* for accessing external information and models. The outputs from these agents are passed to a team of specialized *Scientist Agents*, each tasked with

TABLE 1 Key components of multi-agent artificial intelligence models used in scientific research.

Model	Primary purpose	Core agents and roles	Key features
General Multi-Agent AI Systems (7)	Enable complex task-solving by dividing research into subtasks	• Brainstorming Agents: generate diverse ideas • Expert Consultation Agents: provide domain-specific advice • Debate Agents: test ideas through adversarial reasoning • Roundtable Agents: seek consensus • Self-Driving Lab Agents: automate full research cycles	Simulates interdisciplinary teams with role diversity and collaborative protocols
AI Co-Scientist (8)	Generate, evaluate, and refine scientific hypotheses iteratively	• Generation Agent: proposes and synthesizes ideas from literature and • Reflection Agent: provides peer review for novelty and explanatory power • Ranking Agent: performs an elo-style tournament of hypotheses • Proximity Agent: clusters and de-duplicates • Evolution and Meta-Review Agents: iteratively refines and gives oversight	Tournament-based evaluation, agent self-optimization, and meta-analysis feedback loops
AstroAgents (9)	Analyze large molecular datasets for hypothesis generation	• Data Analyst Agent: identifies patterns • Planner Agent: delegates data segments • Scientist Agents: generate hypotheses for assigned data • Literature Review Agent: synthesizes key publications • Accumulator Agent: concatenates hypotheses • Critic Agent: evaluates novelty and validity	Strong emphasis on modular task delegation, structured outputs, and literature-grounded critique
SpatialAgent: Biomedical Research Agents (10)	Assist scientists in biomedicine through structured collaboration	• Memory Agent: stores long-term goals and short-term execution context • Planning Agent: decomposes user queries, reasoning, and self-reflection to refine strategies • Action Agent: executes tasks using tools, databases, and code, retrieves datasets, performs analyses, integrates outputs from multiple sources	Combines simulation, physical devices (labs), and domain-specific AI agents in a closed research loop

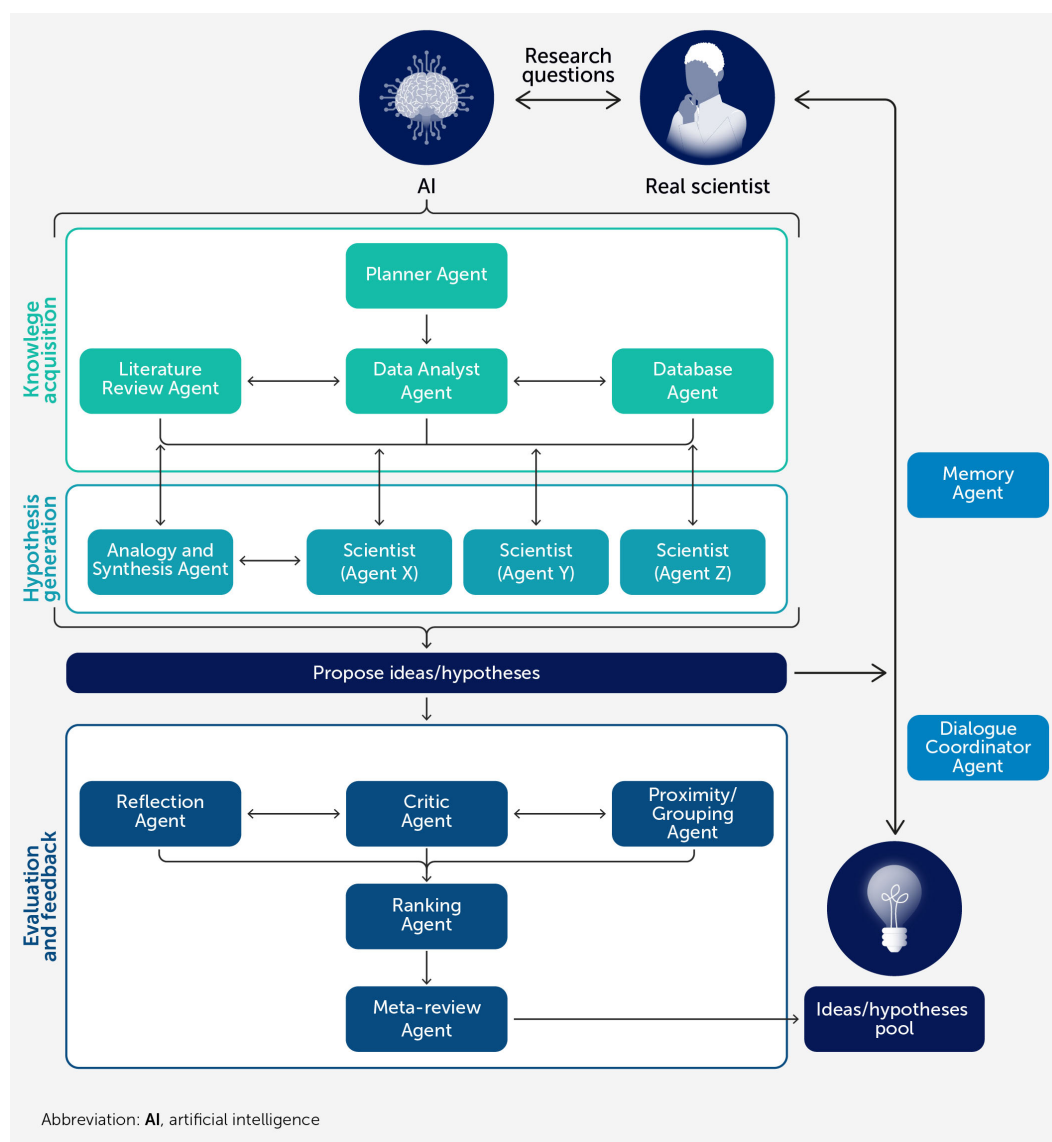


FIGURE 3

Schematic of a proposed multi-agent system for hypothesis generation and experiment design. The system features a *Planner Agent* that decomposes research problems and delegates tasks to specialized agents: *Literature Review*, *Data Analyst*, and *Tool/Database Agents*. Results from these agents are used by *Scientist Agents* to generate structured hypotheses, while an *Analogy and Synthesis Agent* contributes interdisciplinary insights to enhance creativity.

generating structured hypotheses within defined research areas. To foster creativity and interdisciplinary insight, an *Analogy and Synthesis Agent* searches for related concepts across disciplines, enriching the hypothesis pool.

The generated hypotheses are evaluated through multiple lenses: a *Reflection Agent* simulates peer review, a *Critic Agent* assesses empirical validity and methodological rigor, a *Ranking Agent* performs a tournament-style evaluation, and a *Proximity and Grouping Agent* identifies and eliminates redundancies and promotes diversity. *Evaluation Agents* in multi-agent AI systems can engage in expert consultation (e.g., one agent can query another specialized agent and/or a human can critique the results), structured debates (weighing competing hypotheses), and deliberate discussions (reaching consensus on management strategies) (7, 10). Importantly, real scientists should be part of this process by interacting with the system, providing inputs, and critiquing the generated hypotheses.

A *Meta-Review Agent* aggregates these evaluation results and ranks the hypotheses. A *Dialogue Coordinator Agent* manages agent communications during deliberation rounds, while a *Memory Agent* stores prior outputs and insights to support continual learning. This architecture supports an end-to-end loop of hypothesis generation, evaluation, and refinement, simulating the dynamics of a collaborative and adaptive scientific research team.

Potential roles and applications of multi-agent AI systems in soil science

Building on the current foundation of AI tools and inspired by agent-based models from other disciplines, we see huge potential for

multi-agent AI systems to assist in soil science research. These agents, functioning as integrated systems, could help address complex challenges that often exceed the capacity of scientists or are too difficult to solve using isolated tools. With the ability to coordinate data collection, conduct advanced analyses, formulate hypotheses, and interact with digital, human, and potentially even physical systems, AI agents offer new avenues for investigating and understanding soil processes. Below, we highlight several promising applications.

Integrated soil digital twin agents

A multi-agent AI system could serve as a central hub for soil monitoring, continuously orchestrating data acquisition from diverse sources, including networks of *in-situ* and proximal sensors, as well as satellite data streams capturing multi- or hyperspectral imagery.

Continual learning and adaptation are essential for agents operating in dynamic soil environments. As new data are streamed from sensors or experiments, agents must be able to incorporate this information to refine their internal models, update predictions, and adjust ongoing strategies. For instance, an agent managing irrigation could learn from moisture sensor feedback and weather forecasts to optimize water delivery, adapting its approach throughout the growing season. Similarly, an agent monitoring temporal soil conditions could adapt its assessment based on long-term trends observed in sensor data and remote sensing imagery, potentially identifying emerging degradation issues earlier than traditional methods. It could also simulate future scenarios based on different management strategies.

A multi-agent AI system could be tasked with fusing this multimodal data to create a digital twin for monitoring and generating *in silico* experiments (27, 41). Algorithms could detect subtle spatial and temporal patterns based on real-time data, identifying anomalies indicative of issues such as nutrient depletion, water stress, compaction, or erosion hotspots (42). Beyond simple detection, the agent could perform integrated soil assessments from surface to subsoil conditions using multiple indicators. When combined with process-based models, an AI agent could run *in silico* experiments to test new land management options or model soil system responses to climate extremes. The system could then generate dynamic, high-resolution maps and actionable reports for land managers and researchers, far surpassing current manual or semi-automated approaches.

Soil microbiome analysis agents

In the biological frontier, multi-agent AI systems could tackle the complexity of soil microbial communities and their functions. Integrating high-throughput sequencing data (metagenomics or metatranscriptomics) with detailed environmental parameters (i.e., soil chemistry, mineralogy, moisture, temperature, or vegetation types), the system could employ ML models to identify key microbial taxa or functional genes that serve as sensitive indicators of soil health, nutrient cycling efficiency, or disease suppressiveness (43). It could help unravel complex microbe–microbe, plant–microbe, or soil–microbe interactions; predict the

functional consequences of community shifts caused by land management (such as the use of herbicides or amendments) or climate change; and guide the development of targeted microbial inoculants (44).

AI could enhance soil microbiome research by uncovering the structural and functional potential of vast microbial protein datasets. Soil microbiomes contain vast, poorly characterized microorganisms, many of which produce proteins with unknown functions. AI models could be used to predict protein structures from metagenomic data and infer protein function by identifying structural similarities to known proteins. This would contribute to a better understanding of microbial ecology and ecosystem services and to the development of precision soil management tools grounded in protein-level insights.

Multi-agent AI could assist in formulating testable hypotheses based on existing knowledge and incoming data, such as whether a specific microbial consortium enhances nutrient availability under drought conditions, and design strategies for testing them. Multi-agent systems could therefore help researchers to better understand continent-wide microbial distributions and how these relate to soil–plant–climate interactions, thereby assuming a “whole-ecosystem approach”. They could then plan efficient strategies to test these hypotheses, perhaps by designing optimal field sampling campaigns, specifying parameters for targeted laboratory experiments, or setting up *in silico* experiments using simulation models.

Climate change impact and adaptation agents

To address global challenges, a multi-agent AI system could integrate climate model projections with soil process models to forecast the impacts of rising temperatures and altered precipitation patterns on key soil properties, such as organic carbon stocks, moisture regimes, and nutrient availability across different regions. It could also evaluate the effectiveness of various adaptation strategies, such as drought-tolerant cropping systems or water conservation techniques, under future climate scenarios. Importantly, feedback on soil responses to climate change [such as loss of soil organic carbon (SOC) and increased heat transfer in the soil] is needed. Furthermore, such an agent could provide essential support for monitoring, reporting, and verification of soil carbon sequestration (45). Current broad nutrient applications could be transformed through AI-designed soil sampling strategies, producing more detailed information that would enable fertilization rates to be optimized in light of both local conditions that reduce leaching and greenhouse gas emissions.

The common thread across these applications is a shift toward integrated, reasoning systems capable of handling complexity and automating workflows beyond the capacity of current tools. However, a key concern is how AI agents will perform under novel or unprecedented scenarios, such as extreme flooding or other climate-induced events, that fall outside the domain of their training data. In the absence of physical model constraints, predictive reliability may degrade under such conditions. This

emphasizes the continuing need for expert oversight, domain knowledge, and hybrid approaches that combine data-driven insights with mechanistic understanding.

Hypothesis generation and experimental design agents

Multi-agent AI could facilitate knowledge discovery through automated literature analysis and synthesis (46–48). Leveraging LLMs and knowledge graphs, AI could continuously mine the vast body of soil science literature, experimental databases, and real-time monitoring data to identify knowledge gaps and propose novel, testable hypotheses about soil processes.

These systems could then move from hypothesis generation to experimental design for validation. Critically, multi-agent systems must function collaboratively with human soil scientists. The goal is not to replace human expertise but to augment it (5). Agents should be able to communicate their reasoning, present findings clearly, and solicit and incorporate expert feedback. The following section demonstrates the use of such a system.

Scientific hypotheses generation case study: soil carbon saturation research

To demonstrate the feasibility of multi-agent AI systems for hypotheses generation in soil science, we provide an example in which an AI agent system was tasked with a research question. SOC sequestration is increasingly recognized as a key strategy for mitigating climate change and enhancing soil health (49). A central concept of organic carbon persistence is soil carbon saturation, particularly regarding mineral-associated organic carbon (MAOC) (50). This concept suggests that mineral surfaces, especially within clay and silt fractions, have a finite capacity to form organo-mineral complexes due to limited reactive surface area. However, its operational relevance is under debate. Empirical studies by Begill et al. (51), Heinemann et al. (52), and Poeplau et al. (53) challenge the idea of a clear saturation plateau, showing near-linear increases in MAOC even under high carbon inputs, implying that biological and environmental constraints may often limit SOC accrual before theoretical saturation is reached. Conversely, Cotrufo et al. (54) maintain the physical validity of the saturation concept, arguing that observed inconsistencies stem from methodological artefacts, such as the misclassification of particulate organic matter (POC) as MAOC, and emphasize the need to identify real-world factors that prevent soils from reaching their saturation potential.

To explore this issue, we presented this problem to Manus AI, a general-purpose multitask AI agent (55). Manus AI is a multi-agent system built with a transformer-based large language model, organized into three coordinated agents, namely *Planner*, *Execution*, and *Verification*, that collaboratively break down, perform, and validate tasks. It is designed to execute complex, multi-step tasks across various domains independently. It can use external tools, including web browsers, to gather knowledge and information.

For our purposes, we used Manus AI 1.4 to generate a set of scientific hypotheses aimed at improving our understanding of soil carbon saturation and whether it is a useful concept, particularly in the context of agricultural soils under climate change. The prompt and interactions with Manus AI are provided in the [Supplementary Material](#). The AI system was prompted to draw on recent scientific literature (both within and, more importantly, beyond soil science), generate a set of contrasting scientific hypotheses, simulate a peer review process (Reflection, Critic, Proximity, and Grouping) (Figure 3), and rank the hypotheses based on novelty, feasibility, plausibility, and scalability.

Manus AI provided the following steps in its process:

- *literature review*. Identification and analysis of recent scientific publications on soil carbon saturation, mineral-organic matter interactions, adsorption phenomena, and related topics.
- *hypothesis generation*. Development of five pairs of contrasting hypotheses addressing key uncertainties and debates around soil carbon saturation.
- *simulated review*:
 - *Reflection Agent*. Assessed hypotheses for clarity, logical consistency, and alignment with the research question.
 - *Critic Agent*. Evaluated hypotheses for empirical validity, testability, and scientific rigor based on current evidence.
 - *Proximity and Grouping Agent*. Analyzed hypotheses for conceptual overlap, redundancy, and overall diversity.
- *hypothesis ranking*. Synthesized the reviews and evaluated the hypotheses against criteria of novelty, feasibility, plausibility, and scalability.

Hypotheses generation on soil organic carbon saturation

Based on its analysis of recent literature from soil science and related fields (51, 54, 56, 57), Manus AI generated five pairs of hypotheses (Table 2). The hypotheses explore contrasting views on soil carbon saturation, focusing on the following themes:

- the relevance of effective versus theoretical MAOC capacity (H1);
- biological and chemical controls on MAOC formation (H2);
- climate change impacts on carbon persistence and vulnerability (H3);
- interdisciplinary mechanisms involving adsorption and co-precipitation (H4);
- management strategies based on input quality versus saturation status (H5).

The themes span both fundamental concepts reframed for practical relevance and more novel, cross-disciplinary ideas. For example, H1 offers a pragmatic reinterpretation of the carbon saturation concept, and H3 proposes responses to climate change based on a soil's saturation status. H2 challenges the traditional

TABLE 2 A summary of artificial intelligence-generated scientific hypotheses on the concept of MAOC saturation.

Hypothesis theme	Hypothesis	Key proposition	Implication
H1: effective vs theoretical saturation	H1a: effective dominance	Effective MAOC capacity, shaped by climate and management, is more relevant for short- to medium-term carbon sequestration	Prioritize field-measured constraints over theoretical models in current sequestration efforts
	H1b: theoretical relevance	Theoretical maximum MAOC sets long-term limits; understanding the gap is essential for future potential	Use theoretical benchmarks for long-term planning and modeling of extreme scenarios
H2: biological and chemical controls	H2a: microbial bottleneck	Microbial processing limits MAOC formation more than mineral availability, even in unsaturated soils	Enhance microbial efficiency to increase MAOC accrual
	H2b: OM chemistry dominance	OM composition has stronger influence than minerals; some OM bypasses mineral binding	Rethink MAOC definition; optimize OM inputs for chemical quality
H3: climate change impacts	H3a: climate reduces effective capacity	Warming and precipitation shifts reduce effective MAOC by accelerating decomposition and altering soil biogeochemistry	Climate adaptation is needed to preserve carbon under changing conditions
	H3b: vulnerability near saturation	Saturated soils are more vulnerable to loss under climate stress; unsaturated soils retain potential	Target vulnerable soils for protection; focus inputs on unsaturated soils
H4: interdisciplinary mechanisms	H4a: surface chemistry analogy	Adsorption models from colloid science better explain MAOC formation than linear models	Integrate surface science for more accurate MAOC prediction
	H4b: nucleation/co-precipitation role	Co-precipitation with iron and aluminum oxides is a key, and often overlooked, MAOC stabilization process	Consider non-adsorptive pathways in carbon stabilization strategies
H5: practical management implications	H5a: input focus	Carbon input quality and decomposition control matter more than mineral capacity in unsaturated soils	Use diverse, quality inputs and soil conservation practices
	H5b: saturation-aware management	Knowing soil saturation status is vital; near-saturation soils need strategies distinct from unsaturated ones	Tailor practices based on saturation level to optimize sequestration

Abbreviations: **MAOC**, mineral-associated organic carbon; **OM**, organic matter

mineral-centric view of MAOC formation by emphasizing microbial processing and OM chemistry as primary constraints. H4 draws on mechanisms from surface chemistry and geochemistry, which are less explored in soil carbon models, and H5, while the most operationally relevant, builds on established management principles.

Among the hypotheses outlined within the themes, H1b, H3b, and H5a stand out as novel (Table 2), as they highlight underexplored dimensions of soil carbon research. H1b emphasizes the long-term significance of theoretical MAOC capacity under high inputs or land-use scenarios, a concept often overlooked in favor of short-term, field-based studies. H3b introduces a saturation-sensitive risk perspective, suggesting that near-saturated soils may be more vulnerable to carbon loss under climate change. Some of the hypotheses are interrelated as, in practice, the findings from H3a and H3b would influence the feasibility of H1b, for example. H5a emphasizes the practical importance of maximizing high-quality carbon inputs in unsaturated soils, a widely accepted practice yet rarely formalized or directly compared to saturation-based management strategies in research.

Simulated agent reviews

The generated hypotheses then underwent a simulated multi-agent review process to evaluate them from various perspectives, as summarized in Table 3. The *Reflection Agent* reviewed the hypotheses for clarity, logical consistency, internal coherence, and

alignment with the overall research question. The *Critic Agent* evaluated the hypotheses for empirical validity, testability, and scientific rigor, drawing on the analyzed literature and identifying potential challenges or contradictions. The *Proximity and Grouping Agent* reviewed the hypotheses for conceptual overlap, redundancy, and overall diversity and suggested potential groupings or refinements.

In summary, the simulated multi-agent reviews found the hypotheses to be clear, coherent, and diverse, empirically varied but scientifically valuable, with several requiring advanced methods for testing, and well-differentiated with no major redundancy, supporting a broad and balanced research agenda.

Hypotheses ranking

Based on simulated reviews and evaluations of novelty, feasibility, plausibility, and scalability, the hypotheses were ranked according to:

- **Novelty:** degree to which the hypothesis challenges existing paradigms.
- **Feasibility:** practicality of testing with current methods and resources.
- **Plausibility:** alignment with existing empirical and theoretical knowledge.
- **Scalability:** potential to generalize across soil types, climates, and management regimes.

TABLE 3 A summary of the simulated agent reviews for the generated hypotheses on soil organic carbon saturation.

Agent type	Key findings per hypothesis theme*	Conclusion
Reflection Agent	• H1: clear, relevant contrast • H2: thoughtful mechanistic depth, especially around OM chemistry • H3: directly addresses climate impacts, well-articulated • H4: strong integration of novel, external mechanisms • H5: clearly practical, with strong dual-contrast	Hypotheses are clear, internally coherent, and diverse, providing a solid conceptual base
Critic Agent	• H1: H1a has good support; H1b is conceptually sound but testing needs modeling • H2: plausible but hard to disentangle; requires isotopic labelling/ OM characterization • H3: H3a is well-supported; H3b is logical but under-tested and needs long-term data • H4: H4a is theoretical but needs soil validation; H4b is promising but scaling is difficult • H5: H5a is well-supported in depleted soils; H5b is conceptually valid but needs operational metrics	H1a, H3a, and H5a are the strongest empirically; H2 and H4 need advanced experimentation; all are valuable but require rigorous testing
Proximity and Grouping Agent	• Linkages: H1 ↔ H5 (saturation vs. management); H2 ↔ H4 (mechanistic overlaps) • No redundant hypotheses identified; good thematic spread across conceptual, mechanistic, environmental, and practical dimensions	Hypotheses are diverse and complementary; merging is not recommended; all contribute uniquely to a broad research agenda

Abbreviation: **OM**, organic matter
*Hypothesis themes: **H1**, effective vs. theoretical saturation; **H2**, biological and chemical controls; **H3**, climate change impacts; **H4**, interdisciplinary mechanisms; **H5**, practical management implications. Hypotheses: **H1a**, effective dominance; **H1b**, theoretical relevance; **H2a**, microbial bottleneck; **H2b**, OM chemistry dominance; **H3a**, climate reduces effective capacity; **H3b**, vulnerability near saturation; **H4a**, surface chemistry analogy; **H4b**, nucleation/co-precipitation role; **H5a**, input focus; **H5b**, saturation-aware management

TABLE 4 A summary of hypothesis ranking on soil organic carbon saturation.

Rank	Hypothesis theme	Novelty	Feasibility	Plausibility	Scalability	Justification
1	H1 : effective vs. theoretical saturation					Central to current debates; strong plausibility and broad relevance make it a top priority despite moderate feasibility
2	H3 : climate change impacts					Strong relevance to agriculture and climate; widely applicable and supported by trends
3	H5 : practical management implications					High real-world applicability, actionable, and easy to test; ranks highly despite limited novelty
4	H2 : biological and chemical controls					Mechanistically rich and novel but difficult to test and generalize widely.
5	H4 : interdisciplinary mechanisms					Conceptually novel with interdisciplinary appeal but faces testing, scaling, and validation barriers

Legend: High Medium-high Medium Low-medium

The final ranking (Table 4) highlighted H1(effective vs theoretical saturation) and H3 (climate change impacts) as particularly promising avenues for research due to their high relevance, plausibility, and scalability, despite moderate feasibility challenges. H5 (management implications) also ranked highly due to its high feasibility and practical relevance. H2 (biological/chemical controls) and H4 (interdisciplinary mechanisms), while highly novel and plausible for advancing fundamental understanding, face greater hurdles in terms of empirical testing and scaling.

A comparison with expert opinions

After our AI task was completed, a review by Georgiou et al. (58) was published, summarizing the current conceptual understanding of soil carbon saturation. The paper discusses factors controlling carbon inputs and outputs to soil MAOC. The review reinforces the view that

MAOC formation depends on the quantity and chemical composition of inputs from plant and microbial sources, as well as the physical and chemical properties of the mineral matrix. MAOC formation and destabilization are further influenced by soil conditions and disturbances. Table 5 summarizes the conceptual understanding of soil MAOC saturation based on Georgiou et al. (58), comparing it with the AI-generated hypotheses.

Most of the concepts reviewed by Georgiou et al. (58), except for the steady-state concept, are included in the AI-generated hypotheses (Table 2). H1a and H1b align with core soil carbon saturation concepts but emphasize different aspects. H1a prioritizes effective capacity as the most relevant limit of carbon sequestration under real-world climate and management constraints, deeming it more practical than theoretical models. In contrast, H1b stresses the long-term significance of the theoretical mineral capacity as a boundary for maximum sequestration, especially under high carbon inputs or land-use change.

TABLE 5 The conceptual framework for soil carbon saturation according to Georgiou et al. (58) and alignment with artificial intelligence-generated hypotheses.

Concept	Definition	Key Controls	Implications	Representation in AI-derived hypotheses*
Theoretical mineral capacity	Maximum potential mineral-associated organic carbon (MAOC) storage based solely on mineral content, independent of environmental conditions	Clay + silt content, mineralogy	Represents the absolute upper limit for MAOC; difficult to quantify directly	H1b
Maximum observed capacity	Highest MAOC levels observed globally under existing climate and management conditions	Clay + silt, mineralogy, current carbon inputs	Used as a practical proxy for theoretical capacity; may underestimate true limit	H1a
Effective capacity	Context-dependent apparent MAOC limit under current management and climate	Management, vegetation, microbes, moisture, temperature, and pH	May increase with better conditions; useful for assessing local sequestration potential	H1a
Steady-state	Balance between MAOC inputs and outputs over time under stable conditions	All environmental and biological factors	Does not imply capacity is reached, just that MAOC remains stable over time	Not explicit
Carbon input-response saturation	Plateauing of MAOC with increasing carbon input over time	Carbon input quantity/quality, microbial efficiency, and mineral reactivity	Indicates proximity to capacity; needed to confirm saturation status	H2a, H2b, H5a
Saturation and vulnerability	Degree of MAOC saturation may affect sensitivity to disturbance	Nature of organo-mineral bonds and carbon saturation status	Unclear if higher saturation increases or decreases vulnerability; likely context-dependent	H3a, H3b
Representation in models	MAOC saturation incorporated through isotherms or empirical constraints in SOC models	Model structure, parameterization, and microbial processes	Critical for predicting carbon responses to climate and land use; model assumptions strongly affect outputs	H4a

*Hypotheses: **H1a**, effective dominance; **H1b**, theoretical relevance; **H2a**, microbial bottleneck; **H2b**, OM chemistry dominance; **H3a**, climate reduces effective capacity; **H3b**, vulnerability near saturation; **H4a**, surface chemistry analogy; **H4b**, nucleation/co-precipitation role; **H5a**, input focus; **H5b**, saturation-aware management

Hypotheses H2a, H2b, and H5a collectively emphasize that carbon input–response saturation is governed by more than just mineral surface availability. H2a highlights a microbial bottleneck, H2b focuses on the importance of OM chemistry in governing soil carbon saturation, and H5a supports increased, diverse carbon inputs as a practical strategy for carbon-depleted agricultural soils. However, it also indicates that, without addressing microbial and chemical constraints, saturation thresholds may still limit sequestration efficiency. The role of carbon use efficiency and microbial processing for MAOC formation (H2a) aligns with the Microbial Efficiency-Matrix Stabilization framework by Cotrufo et al. (59).

Hypotheses H3a and H3b engage with the concepts of soil saturation and vulnerability (58) in the context of climate change. H3a suggests that climate change (e.g., warming and altered precipitation) reduces a soil's effective MAOC capacity by accelerating decomposition and altering biotic and abiotic conditions. H3b highlights that soils near effective saturation are especially vulnerable to climate pressure, as destabilization of less-protected POC and some MAOC becomes more likely. Regarding hypothesis H3a, Rocci et al. (60), in a meta-analysis, could not find a significant effect of elevated CO₂ and temperature on MAOC, while the effect of changes in precipitation regime were inconclusive due to a lack of sufficient data. Their findings underscore the need to pursue this line of research and support AI ranking. In relation to H3b, a study indicates that SOC vulnerability increases near saturation, especially when stabilization mechanisms rely on weaker or outer-layer interactions (61). Martin et al. (62)

recommended prioritizing residue returns in unsaturated cropland soils and to protect SOC in forests and unimproved grasslands, given their high stocks and relatively high saturation levels. Georgiou et al. (58) therefore conclude that the effect of MAOC saturation on MAOC vulnerability remains uncertain and is highly context-dependent, requiring further research.

Hypothesis H4a (surface chemistry analogy) posits that classical surface chemistry principles, such as adsorption isotherms (e.g., Langmuir and Freundlich models), predict MAOC formation and saturation more accurately than simple linear regressions based solely on fine fraction content (63). This is further confirmed by Georgiou et al. (58), who advocate for mechanistic, process-based modeling frameworks that account for heterogeneous surface reactivity, organo–organic layering, and non-linear carbon loading behavior.

Summary

This process demonstrates how a multitask AI system can effectively support scientific hypothesis generation and evaluation through a structured, multi-agent framework. One of the most immediate benefits is the acceleration of early-stage research. AI systems can help researchers gather information and rapidly generate hypotheses that are grounded in empirical evidence and theoretical frameworks. This could reduce the time and effort typically required to transition from exploratory reading to focused scientific inquiry.

Equally important is the enhanced rigor introduced through simulated peer review. This needs to be further improved through a

step-by-step sequence where researchers evaluate the basis of the hypotheses. This step requires human input and interaction. For example, soil scientists stated that they would like to see a more fundamental understanding of interactions between clay minerals and OM, as most studies use only clay content to determine or evaluate carbon stock. However, it remains uncertain whether the hypotheses generated by AI are entirely novel or simply well-synthesized from existing knowledge. The “black box” nature of the AI system also does not allow for probing of where the knowledge was derived from.

Challenges and future directions

While the potential for AI agents to revolutionize soil science is vast, realizing this vision requires overcoming significant technical, practical, and ethical challenges. As with any tool, multi-agent AI systems require appropriate training and guidelines to ensure responsible and effective implementation. Addressing these limitations will be crucial for developing robust and widely accessible agent-based systems. Minasny et al. (5) outlined a framework on how AI could be used to assist soil science research.

Data remains a fundamental challenge. AI agents, particularly those employing deep learning, thrive on large, high-quality datasets (64). However, comprehensive soil data are often scarce, fragmented, or inconsistent across different regions and measurement protocols. Issues of data heterogeneity (combining point samples, sensor streams, remote sensing imagery, and laboratory analyses), lack of standardization, and limited data-sharing practices hinder the development of generalizable models (28). Consequently, the success of agent-based systems is often limited by the availability of well-documented, ground-truth reference data rather than by data volume from proximal and remote sensors. Future efforts must focus on establishing standardized data formats and protocols, promoting open data initiatives, and developing AI techniques that are adept at learning from sparse, noisy, or multimodal data. Privacy-preserving approaches such as federated learning, secure multiparty computation, and differential privacy can enable collaborative model development without direct disclosure of data (4). Blockchain can serve a limited governance role by supporting provenance tracking, access control, and auditability of model updates (65). These approaches could address private policy issues and consolidate private data from companies.

Model interpretability and trustworthiness are paramount, especially for agents designed to support critical decision-making in agriculture and environmental management. The “black box” nature of many complex AI models can be a barrier to adoption. Developing and implementing explainable AI (XAI) methods tailored to soil science applications is essential (66). Current XAI for LLMs and generative models mainly provide transparency and provenance rather than explanations of internal reasoning. While this can improve trust and usability, it does not offer causal insight into decision processes, reinforcing the need for human oversight and uncertainty-aware deployment (67).

Predictive uncertainty in multi-agent workflows remains insufficiently explored. Sensitivity to prompts, stochastic planning, variable evidence quality, and measurement errors can propagate

through agent chains, increasing the risk of spurious correlations in a data-poor and methodologically heterogeneous domain such as soil science. Uncertainty extends well beyond data quality to include structural assumptions and the reliability of the scientific literature itself. These challenges underscore the necessity of uncertainty-aware workflows and clearly defined human-in-the-loop processes, where expert judgement guides problem formulation, evaluates evidence quality, and contextualizes AI outputs. A framework is suggested in Minasny et al. (5).

Integrating AI agents with physical systems presents another barrier. While agents can excel at analyzing data and running simulations, extending their capabilities to interact with the real world (for instance, by controlling automated soil sampling robots, managing sensor networks, or directly interfacing with laboratory equipment) requires significant advances in robotics, sensor technology, and cyber-physical systems integration (68). Bridging the gap between digital intelligence and physical action is key to realizing concepts like the “self-driving lab” in soil science.

Computational cost and accessibility are practical concerns. Training large AI models and running complex agent systems can be computationally intensive, requiring significant resources that may not be available to all researchers or end-users. Developing more efficient algorithms, leveraging cloud computing platforms, and creating user-friendly interfaces are necessary to ensure equitable access to the benefits of AI agent technology. Nevertheless, AI computations require substantial energy and water for cooling systems, resulting in a significant carbon footprint (69).

Ethical considerations must be proactively addressed throughout the development and deployment lifecycle. Concerns include potential biases in algorithms trained on unrepresentative data, issues of data privacy and ownership, the equitable distribution of benefits derived from AI, and establishing clear lines of responsibility when agent-driven decisions lead to unintended consequences. Scientists also need to assess the AI systems’ outputs and the real-life implications for local communities within a given cultural and socio-economic context. Full use of AI in the scientific method, from hypothesis generation to publication, raises questions about whether researchers truly internalize knowledge produced by AI. There is a risk that scientists may not fully understand AI-derived insights, especially as systems grow more complex. The transfer of knowledge from AI to human researchers is crucial. Without this, there will be ambiguity in attributing authorship and intellectual ownership. An additional risk lies in excessive reliance on AI-generated hypotheses. As Messeri and Crockett (70) argue, assuming that AI has a deeper understanding, broader hypothesis coverage, or more objectivity than it does may lead to a “monoculture of knowers” and bias the scientific process. Scientists should remain active learners and critical thinkers, using AI as an assistive—not substitutive—tool. A framework for responsible AI development in soil science is needed.

Furthermore, effectively grounding AI agents in fundamental scientific knowledge remains a challenge. While LLMs can process vast amounts of text, ensuring they correctly apply core soil science principles [i.e., climate, organisms, relief, parent material, and time, collectively known as the CLORPT factors of soil formation (71)], it still requires sophisticated knowledge integration techniques, potentially involving knowledge graphs or hybrid AI approaches.

Agents must be more than pattern recognizers; they need a degree of scientific understanding.

Creativity as an essential component of the (human) scientific process should also be nurtured, especially since this remains a limitation of multi-agent AI systems. AI models are fundamentally dependent on the data they are trained on. While these agents can autonomously search for and retrieve literature, their effectiveness is shaped by how they access, filter, and prioritize sources. This data-dependency constrains their ability to think “outside the box”, a quality often crucial for scientific breakthroughs. Although AI excels at recombining and synthesizing existing ideas, its capacity for true creativity and the generation of genuinely novel concepts remains uncertain. One potential strength, however, lies in AI’s ability to explore knowledge across disciplines that are rarely considered by soil scientists, thereby expanding the conceptual search space. The central question remains: can AI genuinely create or does it merely reconstruct and reconfigure what is already known?

A pressing issue emerging from the rise of ML and AI over the past two decades is how scientists can maintain a strong foundation in traditional soil science while leveraging AI technologies. A noticeable trend has been the decline in fundamental disciplinary education, as students and professionals are increasingly required to navigate the sophisticated world of ML and AI. This shift has affected the depth of background knowledge among emerging professionals, sometimes making it difficult to interpret or explain research outcomes meaningfully (72).

In this context, AI has the potential to ease the burden by automating time-intensive preparatory tasks, such as literature review and scenario development (as illustrated in the previous section). While AI may contribute to this “fast science” trend, it could also support the “slow science” movement by improving the work-life balance by saving time. Researchers could focus more on deepening their understanding of core soil science principles.

The scientific community must establish mechanisms to ensure foundational knowledge is not lost in the process. Overreliance on AI tools risks cognitive offloading (73). Balancing AI-driven efficiency with rigorous disciplinary training is crucial to maintaining scientific integrity and achieving long-term progress. Imagination and creativity need to be fostered. AI can supercharge soil science but only if we pair its speed with core field knowledge.

Finally, strengthening collaboration is key. Progress requires breaking down disciplinary silos and encouraging close collaboration between soil scientists, AI researchers, computer scientists, engineers, and social scientists. Platforms that facilitate this interaction, such as the AI Co-Scientist, could help develop solutions that are not only technically sound but also relevant, usable, and adopted by the end-user community. Building shared infrastructure, benchmark datasets, and open-source tools will further accelerate progress. Adopting open-access, open-source, and open-data practices, guided by the FAIR principles (findable, accessible, interoperable, and reusable), provides an essential foundation for transparency, reproducibility, and inclusive participation, helping to broaden access to the benefits of AI-enabled soil science (74).

Conclusion: cultivating soil discovery with intelligent partners

Soil science is on the brink of a transformative era, fueled by the expanding capabilities of multi-agent AI systems. Unlike traditional ML tools that focus on isolated tasks, these advanced, integrated systems offer a powerful new way to address the complexity and ever-changing nature of soil ecosystems. AI agents can seamlessly integrate multiple sources of data to build dynamic models, generate and test hypotheses, and design adaptive strategies for monitoring and sustainable management. Crucially, they work in partnership with human scientists—augmenting but not replacing their expertise.

These intelligent collaborators can dramatically accelerate the pace of discovery, transforming vast datasets into meaningful insights. By exploring multiple solution pathways and building on existing knowledge, AI can expand the boundaries of scientific exploration while still relying on human judgment to interpret, refine, and apply the findings.

While AI can emulate aspects of expert reasoning, it cannot replace the contextual judgment, creativity, and critical interpretation that human scientists bring to the research process. As such, AI should be viewed as an augmentative tool, enhancing but not substituting human-led scientific inquiry.

To fully realize this promising future, we need to foster interdisciplinary collaboration, ensure equitable access to AI tools, and thoughtfully address ethical challenges. By bridging digital innovation with real-world application, we can unlock new levels of understanding, stewardship, and security for our soils, one of the planet’s most vital and existential resources.

Supplementary material

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Statements

Author contributions

BM: Conceptualization, Writing – original draft, Writing – review & editing, Visualization, Investigation, Validation.

AMcB: Conceptualization, Validation, Writing – review & editing, Writing – original draft, Investigation, Validation.

JAMD: Writing – review & editing, Investigation, Validation.

MRD: Writing – review & editing, Investigation, Validation.

PS: Writing – review & editing, Investigation, Validation.

Data availability statement

The original contributions presented in the study are included in the article/[Supplementary Material](#). Further inquiries can be directed to the corresponding author.

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Generative AI statement

The authors declared that generative AI was used in the creation of this manuscript. The authors declared that Manus AI was used to illustrate a point in this article, specifically to generate an example of hypotheses generation by AI. The prompts were included in [Supplementary Material](#). ChatGPT 4o was employed to assist with improving the clarity, grammar, and overall quality of the English language.

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