AI-Enabled farming systems: Opportunities, limits, and the need for system thinking

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Farming systems are increasingly affected by climate change, resource constraints (e.g., soil constraints), and the need to balance environmental sustainability with expectations for the quantity and quality of agricultural products. In recent years, artificial intelligence (AI) has become an integral component of agricultural systems research, with applications spanning soil system management, crop monitoring, yield forecasting, and optimization of agricultural management practices.[1] While these advancements have expanded analytical capabilities for agricultural systems, they also raise a more challenging question: Does the current widespread application of AI in farming systems promote long-term transformation or merely enhance short-term technical efficiency? This poses new considerations for researchers, government officials, and farmers alike.

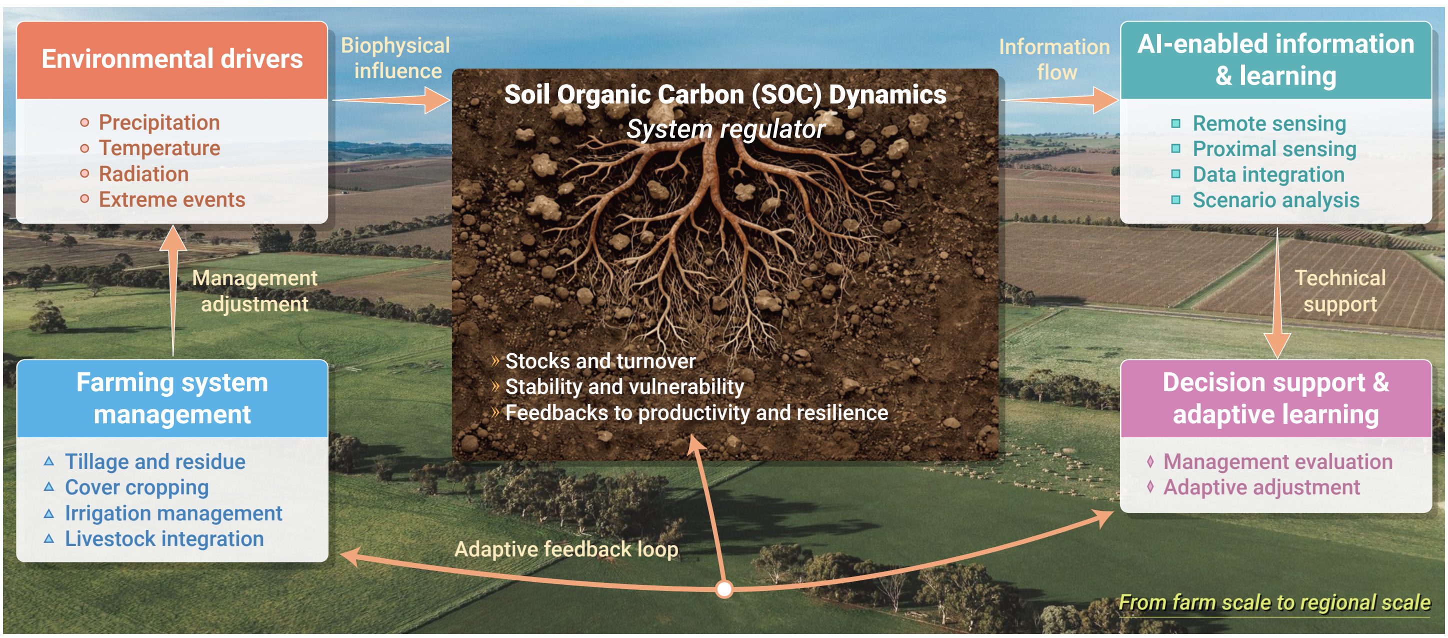

Figure 1. Conceptual framework of AI-enabled climate-smart farming systems centred on soil organic carbon (SOC) The framework illustrates the coupled socio-ecological and AI-mediated adaptive control system linking environmental drivers, farming system management, SOC dynamics, information flows, and decision-support processes. Solid arrows denote biophysical influences (e.g., climate and management effects on SOC), while directional information flows represent monitoring and learning processes enabled by sensing and data integration. The adaptive feedback loop connects decision support to management adjustment, enabling iterative system optimisation from farm to regional scales.

FROM CLIMATE-SMART AGRICULTURE TO SYSTEMS THINKING

Climate-Smart Agriculture (CSA) offers a widely accepted framework to address this challenge by balancing productivity, resilience, and climate mitigation.[1] However, in practice, CSA implementation often relies on isolated management practices—such as reduced tillage, cover cropping, irrigation adjustment, or livestock integration—which are predominantly studied and analysed in isolation.[2] The cumulative and interactive effects of these practices at the agricultural system level remain under-researched. This fragmentation limits farming systems' capacity for coordinated responses to climate risks and policy incentives. Against this backdrop, AI should not be viewed as a novel, standalone solution but rather as a supporting element within broader systems-oriented approaches.

LIMITATIONS OF CURRENT AI APPLICATIONS

A critical limitation in many current AI applications in agriculture is their excessive focus on algorithmic performance over systems relevance. Predictive accuracy is often treated as the final goal, with little attention paid to how model outputs guide management decisions or influence long-term system behaviour. Farming systems are shaped by the internecion of environmental drivers, soil processes, agricultural management strategies, and socio-economic factors. Enhancing a single outcome—such as yield or ecological efficiency—does not necessarily translate into greater resilience or sustainability. Without a clear systems perspective, AI risks reinforcing narrow objectives rather than supporting climate-smart decision-making.

SOIL ORGANIC CARBON AS A SYSTEM INTEGRATOR

Within CSA farming systems, soil organic carbon (SOC)—a fundamental and widely regognized of soil health indicator across the sector—provides a practical and conceptually robust integrative framework. SOC can maintain soil structure, soil fertility, water retention, nutrient cycling, and biological activity, while also serving as a key mechanism for mitigating climate change through carbon sequestration.[3] Crucially, SOC responds both to long-term management strategies and short-term climate fluctuations. This dual sensitivity elevates SOC beyond a single evaluation metric: it functions as a systemic linkage, linking management practices to climate-smart goals.

AI-ENABLED SOC MONITORING AND MANAGEMENT

The emergence and widespread application of AI present clear opportunities to enhance SOC-cantered farming system management. Advances in remote sensing and proximital sensing technologies, combined with machine learning, have improved capabilities for characterizing soil spatial variability and monitoring management effects across scales. When integrated with climate data and management records, AI can support the synthesis of diverse information streams that were previously difficult to integrate. These capabilities are particularly crucial for identifying trade-offs between productivity, carbon sequestration, and risk, as well as supporting scenario-based decision-making under climate uncertainty. In Australia, our synthesis of results from 430 farms and over 15,000 soil samples across typical agricultural regions indicates that low-cost estimation methods only function effectively when sensing technologies, sampling designs, and modelling align with agricultural system structures. Precision sampling strategies combined with proximal sensing, machine learning, and remote sensing can estimate farm- and regional-scale SOC content.[4] However, their success depends less on algorithmic complexity and more on how well they reflect management variations and decision-making needs. These experiences demonstrate that AI-driven approaches must be integrated into coherent agricultural system frameworks to truly deliver CSA outcomes.

CONSTRAINTS BEYOND AI

At the same time, the limitations of AI in farming system's applications must be acknowledged. Data-driven models are constrained by factors such as data availability, representativeness, and mismatches in scale between observations and management decisions.[5] Furthermore, farming systems control within social and institutional contexts that cannot be captured by algorithms alone. AI cannot replace agronomic knowledge, farmer experience, governance structures, indigenous knowledge, or emerging environmental changes. Instead, its value depends on enhancing systemic understanding and facilitating learning across time and space. Recognizing these shortages is vital to avoid overconfidence in technological solutions and ensure AI makes constructive contributions to climate-smart transitions in farming system. Experiences from ongoing large-scale SOC assessments further highlights the importance of systems thinking.

A SYSTEMS THINKING FRAMEWORK

This paper then argues that a systems thinking approach offers a pathway to reconcile these opportunities and constraints. Conceptually, CSA farming systems can be viewed as dynamic interactions among environmental drivers, management practices, and SOC dynamics, with information and decision feedback acting as regulators. Within this framework, AI serves as an information interpreter and learning tool, linking sensing, modelling, and decision support for farmers within a closed-loop process. Management interventions influence SOC stocks and stability, while the response of SOC in turn affects system resilience and productivity. AI-driven analytics then help guide adaptive adjustments under changing climatic conditions. Positioning AI within this conceptual framework shifts the focus from algorithmic optimization to system-level intelligence. This perspective aligns AI development with the core objectives of CSA and underscores the necessity for interdisciplinary collaboration among soil scientists, agronomists, data scientists, and policymakers. Crucially, it emphasizes that measuring AI's success in farming systems should not be based solely on predictive accuracy, but rather on its contribution to building resilient, adaptive, and sustainable agricultural systems.

Translating this systems-thinking perspective into practice requires at least three specific implementation pathways. First, integrated multi-source data architectures should be established, linking proximal sensing, remote sensing, farm management records, and climate datasets into interoperable platforms. Such integration enhances cross-scale consistency between observation units and management decision contexts. Second, hybrid modelling frameworks that combine data-driven machine learning with process-based soil–crop models (e.g., carbon turnover or water balance models) should be developed to embed mechanistic understanding within predictive systems. This integration reduces the risk of purely statistical optimisation detached from agronomic processes. Third, AI outputs should be embedded within adaptive decision-support loops, where model predictions are periodically updated based on monitoring feedback, farmer input, and policy signals.[1] This closed loop learning process enables farming systems to adjust under climate variability rather than relying on static recommendations.

CONCLUSION

As climate change and human activities' pressures intensify, the challenge is no longer whether AI can be applied to agriculture, but how to effectively integrate it into farming systems. Building AI-enabled solutions around SOC and climate-smart objectives provides a coherent pathway from isolated applications to integrated system solutions. This shift is crucial for translating technological advances into lasting benefits for farmers, land, and climate resilience. We also anticipate AI will intelligently and instantly empower farmers to achieve efficient management and long-term monitoring of their agricultural systems.

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AUTHOR CONTRIBUTIONS

Yuantong Jia drafted the manuscript, and Ram Dalal, Tong Li and Yash Pal. Dang provided critical revisions and intellectual guidance. All authors contributed to the manuscript and approved the final version.

DECLARATION OF INTERESTS

The authors declare no competing interests.