

Artificial Intelligence and the Optimisation of Crop Rotation Decisions in Small Agricultural Enterprises

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Abstract

Crop rotation is a foundational agronomic practice through which small agricultural enterprises regulate soil fertility, suppress weeds and pests, distribute labour and capital across the season, and buffer against price and weather volatility. Yet rotation planning in such enterprises is frequently reduced to inherited custom or short-horizon intuition, because the combinatorial nature of multi-season allocation, compounded by uncertain yields, prices, and climate, exceeds the deliberative capacity of owner-managers with limited data infrastructure. Artificial intelligence offers a tractable route to formalising and improving these decisions. This abstract synthesises contemporary evidence on the application of AI, machine learning, and associated data-driven methods to the optimisation of crop rotation in small-scale farming contexts, with attention to agronomic, economic, and institutional dimensions. Machine learning models trained on agronomic, meteorological, soil, and remote-sensing data can forecast yields and disease pressure, supplying the probabilistic inputs that rotation optimisers require. Metaheuristic and swarm-intelligence approaches have demonstrated their capacity to solve annual crop planning problems in irrigation schemes, while robust temporal optimisation frameworks address climate uncertainty by generating rotation schedules that remain acceptable across plausible futures rather than optimal for a single forecast. Integrated architectures combining data warehouses, big-data analytics, and decision-support layers translate heterogeneous field records into actionable rotation recommendations, and real-time monitoring frameworks extend such support toward adaptive management within the growing season. For small enterprises, the economic case rests on input savings, yield stability, and improved land-use efficiency rather than on capital-intensive automation, and the literature on precision agriculture indicates that value accrues incrementally through targeted, low-cost interventions. Several constraints temper this promise. Data scarcity and fragmentation, limited digital literacy, and weak connectivity impede model development in small-firm settings, while security threats to agricultural AI systems raise concerns about the integrity of recommendations and the confidentiality of farm records. The build-versus-buy decision facing small and medium enterprises under resource and regulatory constraints further shapes adoption pathways, favouring subscription and advisory models over bespoke system development. Sustainability considerations are twofold: optimised rotations can support soil health, reduced agrochemical dependence, and resilience consistent with regional ecosystem objectives, but optimisation objectives that privilege short-term profit may undermine these gains unless explicitly constrained. The reviewed evidence supports a conclusion that AI-enabled rotation optimisation is technically mature enough for pilot deployment among smallholders, provided that systems are designed around sparse data, explainability, and local agronomic knowledge, and that institutional support addresses skills, trust, and cost-sharing. Future work should prioritise longitudinal field validation, participatory design with smallholders, and the integration of economic and ecological objectives within a single optimisation framework.

Keywords: *Artificial intelligence; Crop rotation optimisation; Small agricultural enterprises; Decision support systems; Precision agriculture; Sustainable agriculture*

INTRODUCTION

Background

Artificial intelligence has moved from experimental novelty to operational necessity across the agri-food value chain,

reshaping how producers, processors, and marketers allocate scarce resources under conditions of biological and climatic uncertainty (Abinaya *et al.*, 2024). The integration of machine learning, remote sensing, and decision-support architectures into farming practice has been documented extensively, with precision agriculture now recognised as a mature field in which data-driven interventions substitute for intuition-based judgement (Monteiro *et al.*, 2021). This shift is not confined to large commercial estates. Small agricultural enterprises, defined here as family-owned or micro-scale farming operations with limited capital, labour, and technical capacity, increasingly confront the same informational demands as industrial holdings while possessing a fraction of the resources required to meet them (Sulima *et al.*, 2025). The strategic position of such enterprises within regional food systems makes their operational efficiency a matter of broader economic consequence, and marketing and development strategies for agricultural enterprises have begun to incorporate digital and analytical capabilities as core rather than peripheral assets (Sulima *et al.*, 2025).

Crop rotation sits at the centre of this transformation. Rotation decisions determine soil fertility trajectories, pest and disease pressure, water and nutrient requirements, and ultimately the economic viability of the enterprise across multi-year horizons. Yet rotation planning in small enterprises is frequently conducted through inherited practice, rule of thumb, or short-term price signals rather than systematic optimisation (Abinaya *et al.*, 2024). Artificial intelligence offers a route to formalise these decisions, encoding agronomic constraints, market expectations, and resource limits into models capable of evaluating thousands of candidate sequences that no human planner could assess manually (Monteiro *et al.*, 2021). The convergence of affordable sensing, cloud computation, and accessible machine learning tooling has lowered the barrier to entry, making optimisation theoretically available to enterprises that could never have commissioned bespoke modelling a decade ago (Sulima *et al.*, 2025).

Problem Statement

Despite this potential, the optimisation of crop rotation decisions in small agricultural enterprises remains under-theorised and inconsistently implemented. Early computational work on annual crop planning demonstrated that metaheuristic techniques, particularly swarm intelligence, could generate feasible and economically superior planting schedules for irrigation schemes where conventional linear programming struggled with combinatorial complexity (Adewumi and Chetty, 2013). These methods established proof of concept but were developed in contexts of relatively homogeneous land holdings and centralised planning, conditions that poorly mirror the fragmented, resource-constrained reality of small enterprises. Contemporary reviews of artificial intelligence in sustainable crop production confirm that the bulk of documented applications address monitoring, disease detection, and yield prediction rather than the sequential, multi-season decision problem that rotation represents (Piekutowska, 2025). The optimisation literature has advanced considerably in data-driven resource use efficiency, yet systematic reviews of machine learning for crop management report persistent gaps between algorithmic capability and farm-level adoption, with small enterprises least represented in both the evidence base and the deployment record (Ugwu *et al.*, 2025).

The problem is therefore twofold. Conceptually, rotation optimisation for small enterprises lacks a coherent framework that reconciles agronomic constraint satisfaction with economic objectives under uncertainty. Practically, the tools that exist are rarely calibrated to the data scarcity, capital limitations, and risk profiles that characterise small-scale operations (Adewumi and Chetty, 2013). Addressing this dual gap requires research that treats the small enterprise not as a scaled-down version of a commercial farm but as a distinct decision environment with its own constraints and optimisation logic (Ugwu *et al.*, 2025).

Objectives

1. To examine the current application of artificial intelligence techniques to crop rotation and crop planning decisions, identifying the algorithmic approaches, data requirements, and performance outcomes reported in the literature (Adewumi and Chetty, 2013; Piekutowska, 2025).
2. To analyse the data analytics and decision-support infrastructure required to operationalise rotation optimisation in small agricultural enterprises, including the integration of heterogeneous agronomic, meteorological, and market data (Chergui and Kechadi, 2022).
3. To assess the sustainability and economic implications of artificial intelligence adoption for small enterprises, situating rotation optimisation within broader debates on regional ecosystem impacts and enterprise financial performance (Pimenow *et al.*, 2025; Voskolupov, 2025).
4. To identify the barriers, risks, and governance considerations that condition the successful deployment of optimisation systems in resource-constrained farming contexts (Gao *et al.*, 2024; Randall *et al.*, 2021).

Research Questions

1. What artificial intelligence methods have been applied to crop rotation and annual crop planning, and how do their data requirements and computational demands align with the capacities of small agricultural enterprises (Adewumi and Chetty, 2013; Piekutowska, 2025)?
2. How can data analytics architectures and decision-support systems be structured to deliver actionable rotation recommendations under the data scarcity and variability typical of small-scale farming (Chergui & Kechadi, 2022)?
3. What sustainability, economic, and risk considerations determine whether artificial intelligence-driven rotation optimisation produces durable benefits for small enterprises rather than transient efficiency gains (Pimenow *et al.*, 2025; Randall *et al.*, 2021)?

Significance

The significance of this research extends across theoretical, practical, and policy domains. Theoretically, it contributes to

the growing body of scholarship examining how artificial intelligence can be harnessed for inclusive and sustainable futures, moving beyond aggregate productivity narratives to interrogate distributional questions of who benefits from algorithmic optimisation (Prakash and Kaur, 2025). The Sustainable Development Goals (SDGs) provide a normative frame within which artificial intelligence applications are increasingly evaluated, and rotation optimisation speaks directly to goals concerning responsible production, zero hunger, and life on land (Ziemba *et al.*, 2024; Deswal and Deswal, 2025). By focusing on small enterprises, the research addresses a population frequently absent from technology-adoption studies yet numerically dominant in many agricultural economies.

Practically, the research offers small enterprise managers and extension services a structured account of what optimisation can and cannot deliver. Big data approaches to weed control and crop protection illustrate that analytical gains are contingent on data quality and interpretive capacity, not merely algorithmic sophistication (van Evert *et al.*, 2017). Clarifying these contingencies helps enterprises avoid costly misadoption. For policymakers and development agencies, the findings inform the design of support programmes that treat digital capability as infrastructure rather than individual purchase, aligning with inclusive innovation agendas (Prakash and Kaur, 2025). The research also contributes to sustainability scholarship by examining whether optimisation reduces input intensity and environmental load or merely redistributes it across seasons and fields (Ziemba *et al.*, 2024).

Scope

The scope of this research is delimited in four respects. First, it concentrates on crop rotation and annual crop planning rather than the full spectrum of farm management decisions, though it acknowledges adjacent applications in monitoring and protection (van Evert *et al.*, 2017). Second, it addresses small agricultural enterprises specifically, excluding large commercial operations except where comparative evidence illuminates scale-dependent effects. Third, the temporal dimension of rotation is treated as central: robust temporal optimisation under climate change uncertainty provides the methodological anchor for evaluating whether proposed solutions remain viable across multi-year horizons rather than single seasons (Randall *et al.*, 2021). Fourth, the research engages with weed science and crop protection only insofar as these interact with rotation sequencing, recognising that artificial intelligence applications in weed science are advancing rapidly and shape the constraint set within which rotations are planned (Zuñiga *et al.*, 2026).

The research does not attempt primary data collection from farming operations; it synthesises and analyses existing scholarship and documented applications. Security and privacy considerations are addressed as governance constraints rather than as technical engineering problems, reflecting the position that threats to agricultural artificial intelligence are as much institutional as computational (Gao *et al.*, 2024). Geographically, the evidence base is international, though the analytical emphasis falls on contexts where small enterprises predominate and where digital infrastructure is unevenly distributed (Randall *et al.*, 2021).

Key Terms

- *Artificial intelligence (AI)*: Computational systems that perform tasks associated with human cognition, including learning, reasoning, and decision-making, applied in agriculture to prediction, classification, and optimisation problems (Rane *et al.*, 2024).
- *Crop rotation optimisation*: The systematic selection and sequencing of crops across seasons and fields to satisfy agronomic constraints while maximising specified objectives such as profitability, soil health, or resource efficiency (Ngo *et al.*, 2020).
- *Small agricultural enterprise*: A farming operation characterised by limited land area, capital, and labour, typically family-managed, with restricted access to specialised technical expertise and digital infrastructure (Бойко *et al.*, 2024).
- *Decision support system (DSS)*: An integrated information system that combines data management, analytical modelling, and user interface components to assist managers in making structured decisions (Ngo *et al.*, 2020).
- *Data-driven crop management*: The use of large-scale, heterogeneous data sources and analytical methods to inform agronomic decisions, encompassing sensing, integration, and interpretation activities (Rane *et al.*, 2024).

Organization

The remainder of the paper is organised as follows. Following this introduction, which has set out the background, problem, objectives, research questions, significance, scope and key terms of the study, the literature review examines the algorithmic families, data requirements and reported outcomes of artificial intelligence in crop planning and rotation, with particular attention to the gap between commercial and small-enterprise applications (Razak, 2024). The review also draws on intelligent systems frameworks for real-time crop monitoring and agricultural resilience to situate optimisation within enterprise decision-making (King *et al.*, 2023). The methodology that follows sets out the research design, sampling, data collection, optimisation modelling and adoption analysis, together with the procedures used to integrate and validate the evidence.

The results and discussion then present the optimisation outcomes, compare algorithmic approaches and data architectures, and examine sustainability implications and adoption barriers, including the conditions under which artificial intelligence adoption by small and medium enterprises yields durable benefit given resource and regulatory constraints (Сидорук, 2023). The discussion also draws out implications for practice, policy and enterprise strategy, including the economic efficiency of land use management and the integration of artificial intelligence into precision agriculture workflows (Mishra, 2025; Shebanina *et al.*, 2025). The paper closes by summarising its findings and contributions, offering recommendations, acknowledging limitations and proposing directions for future investigation

into inclusive and sustainable artificial intelligence deployment in small-scale agriculture.

LITERATURE REVIEW

Foundations: Artificial Intelligence in Agricultural Decision-Making

The conceptual foundations of artificial intelligence in agriculture have been shaped by a diverse body of scholarship that spans food processing, crop production and the strategic management of agricultural enterprises. Abinaya *et al.* (2024) situate AI within the broader food processing value chain, demonstrating that intelligent systems are no longer confined to on-farm agronomy but extend into post-harvest handling, quality control and supply chain coordination. This positioning is significant for small agricultural enterprises because it implies that the benefits of AI adoption are not limited to the field but accumulate across the entire production cycle. Piekutowska (2025) offers a comprehensive review of AI for sustainable crop production, with a particular focus on potato production, and argues that intelligent systems can simultaneously improve yield stability and reduce environmental externalities. The review's emphasis on sustainability is instructive, yet its concentration on a single crop limits its direct transferability to the diversified rotation systems that characterise small enterprises, where multiple crops compete for land, labour and capital within a single planning horizon.

Voskolupov (2025) contributes a theoretical treatment of marketing management at agricultural enterprises, establishing that strategic decision-making in such firms is conditioned by market positioning, resource constraints and managerial capacity. Read alongside Abinaya *et al.* (2024) and Piekutowska (2025), a tension emerges: the technical literature assumes that intelligent systems will be adopted by rational actors seeking efficiency gains, while the management literature reveals that agricultural enterprises are embedded in marketing and organisational logics that may prioritise risk avoidance over optimisation. For crop rotation decisions specifically, this tension is consequential, because rotation planning is simultaneously an agronomic problem and a commercial one. The foundational literature thus establishes the promise of AI but leaves underexplored the question of how small enterprises reconcile algorithmic recommendations with the managerial realities described by Voskolupov (2025). This gap frames the subsequent review of optimisation methods, data infrastructures and adoption barriers.

Optimisation Methods for Crop Planning and Rotation

The methodological core of AI-enabled crop rotation lies in optimisation algorithms that can handle the combinatorial complexity of allocating crops to land across multiple seasons. Adewumi and Chetty (2013) provide an early and influential contribution through their study of swarm intelligence techniques for the annual crop planning problem in a new irrigation scheme. Their work demonstrates that metaheuristic approaches inspired by collective animal behaviour can generate feasible and near-optimal crop plans where conventional linear programming struggles with non-linear constraints and large search spaces. The significance of this contribution for small enterprises is that swarm intelligence methods are computationally modest and do not require extensive historical datasets, making them attractive where data infrastructure is thin. However, the study's context—a newly established irrigation scheme—implies relatively homogeneous land and centralised planning, conditions that differ markedly from the fragmented, heterogeneous plots typical of small farms.

Pimenow *et al.* (2025) extend the analytical frame by examining the impact of AI on the sustainability of regional ecosystems, arguing that optimisation must be evaluated not only against yield or profit but also against ecological externalities such as soil degradation and biodiversity loss. This argument complicates the purely economic objective functions embedded in earlier optimisation work, suggesting that crop rotation models should incorporate sustainability constraints. Ziemba *et al.* (2024) reinforce this position by linking AI deployment to the Sustainable Development Goals, showing that intelligent systems can be aligned with broader policy objectives when their design explicitly incorporates social and environmental criteria. Taken together, these three sources reveal an evolution in optimisation thinking: from feasibility-seeking algorithms (Adewumi and Chetty, 2013) toward multi-objective frameworks that balance productivity with ecological sustainability (Pimenow *et al.*, 2025; Ziemba *et al.*, 2024). The unresolved question is one of operationalisation. Metaheuristic methods were designed for single-objective problems, and extending them to multi-objective rotation planning under sustainability constraints introduces computational and interpretive burdens that small enterprises may be ill-equipped to manage. The literature thus establishes methodological possibility without adequately addressing the translation of multi-objective optimisation into decision support that is usable at enterprise scale.

Data Analytics and Big Data Infrastructures

If optimisation provides the algorithmic engine of AI-enabled rotation planning, data analytics provides its fuel. Chergui and Kechadi (2022) present a big data perspective on crop management, arguing that the volume, velocity and variety of agricultural data require analytical architectures capable of integrating remote sensing, weather records, soil sensors and historical yield data. Their contribution is to formalise the data pipeline that underpins intelligent crop management, from ingestion through to actionable insight. Prakash and Kaur (2025) broaden the discussion by framing AI as a vehicle for inclusive and sustainable futures, emphasising that data-driven agriculture must be accessible to marginalised producers rather than concentrated among large, capital-intensive operations. This inclusivity argument is directly relevant to small enterprises, which risk being excluded from data ecosystems that are designed around industrial-scale farms.

Zuñiga *et al.* (2026) apply the data analytics lens to weed science, offering a multifaceted review of how AI can support weed identification, mapping and management. Their work is pertinent to crop rotation because rotation is itself a weed

management strategy; intelligent systems that can predict weed pressure under different rotation sequences add a dimension that purely yield-oriented models overlook. Synthesising these sources, a layered picture emerges: Chergui and Kechadi (2022) supply the architectural logic, Prakash and Kaur (2025) supply the equity imperative, and Zuñiga *et al.* (2026) supply a domain-specific application that connects data analytics to agronomic practice. A critical tension, however, runs through the trio. Big data architectures assume data abundance, yet small enterprises operate in conditions of data scarcity, with limited historical records and inconsistent digitalisation. The literature acknowledges inclusivity as a normative goal (Prakash and Kaur, 2025) but offers little guidance on how analytics can function when the underlying data are sparse. For crop rotation decisions, this is a material gap, since rotation planning depends on multi-year records that small enterprises rarely maintain systematically. The data analytics literature thus illuminates the potential of intelligent crop management while exposing an infrastructural precondition that many small enterprises cannot yet satisfy.

Climate Uncertainty, Risk and Economic Performance

Crop rotation decisions are made under uncertainty, and the literature has increasingly turned to robust optimisation as a response. Randall *et al.* (2021) address robust temporal optimisation for a crop planning problem under climate change uncertainty, demonstrating that plans optimised for expected conditions may perform poorly when rainfall, temperature and growing seasons shift. Their methodological contribution is to embed uncertainty directly into the optimisation model, generating plans that remain acceptable across a range of climate scenarios rather than optimal for a single forecast. This is a significant advance for small enterprises, which are disproportionately exposed to climate variability because they lack the insurance, diversification and buffer capacity of larger firms. Van Evert *et al.* (2017) approach uncertainty from a different angle, examining big data for weed control and crop protection. Their work shows that data-driven prediction can reduce the risk of crop loss by anticipating pest and weed outbreaks, thereby complementing the temporal robustness that Randall *et al.* (2021) pursue through optimisation.

Бойко *et al.* (2024) ground these methodological debates in financial and economic performance, analysing the determinants of agricultural enterprise viability and proposing policy improvements. Their analysis reminds us that optimisation and risk management are ultimately constrained by financial capacity: a robust rotation plan is of little value to an enterprise that cannot finance the inputs it requires. Read together, these sources construct a three-part argument. Randall *et al.* (2021) establish that uncertainty must be modelled explicitly; van Evert *et al.* (2017) establish that data can mitigate biological risks; and Бойко *et al.* (2024) establish that economic performance mediates whether either form of risk management is feasible. The critical insight is that these literatures rarely converse. Robust optimisation studies seldom incorporate the financial constraints that Бойко *et al.* (2024) document, while financial performance analyses rarely engage with the temporal uncertainty modelling of Randall *et al.* (2021). For small enterprises, this disconnection is problematic because climate risk and financial fragility are experienced simultaneously rather than sequentially. Integrated framework that couples robust rotation planning with enterprise-level financial capacity remains an unmet need in the reviewed literature.

Adoption Barriers: Security, Skills and Resource Constraints

The promise of AI in crop rotation is mediated by adoption barriers that are particularly acute for small enterprises. Gao *et al.* (2024) examine security threats to agricultural artificial intelligence, arguing that intelligent systems introduce vulnerabilities ranging from data poisoning and adversarial manipulation to privacy breaches and model theft. Their position paper is a corrective to techno-optimistic narratives, insisting that the same data dependencies that enable precision also create exposure. For small enterprises, which typically lack dedicated cybersecurity capacity, these threats are not abstract; compromised recommendations could lead to costly rotation errors. Rane *et al.* (2024) survey smart farming applications across AI, machine learning, deep learning and large language models such as ChatGPT, cataloguing opportunities while candidly acknowledging challenges related to cost, connectivity, digital literacy and integration with legacy practices. Their review is valuable for its breadth, though its treatment of small enterprises is embedded within a general discussion rather than foregrounded.

Сидорук (2023) offers the most directly relevant analysis of adoption constraints, examining how small and medium enterprises in Poland, Romania and Moldova choose between creating, commissioning or subscribing to AI solutions under resource and regulatory limitations. This tripartite framing—build, buy or subscribe—is analytically powerful because it recognises that adoption is not a binary decision but a strategic choice shaped by capital availability, regulatory environment and internal capability. The study's regional focus on Central and Eastern Europe resonates with the conditions facing many small agricultural enterprises, where regulatory ambiguity and limited technical expertise constrain options. Comparing the three sources, a layered model of barriers emerges: Gao *et al.* (2024) identify security risks that persist after adoption, Rane *et al.* (2024) identify capability and infrastructure gaps that precede adoption, and Сидорук (2023) identifies the strategic and regulatory calculus that determines which adoption pathway is viable. The critical synthesis is that these barriers interact. An enterprise that lacks digital literacy (Rane *et al.*, 2024) is more vulnerable to security threats (Gao *et al.*, 2024), and an enterprise facing regulatory uncertainty (Сидорук, 2023) may defer adoption altogether. The literature thus establishes that adoption is a compound problem, yet it offers limited empirical evidence on how small agricultural enterprises actually navigate these interacting constraints when making rotation decisions.

Decision Support Systems and Integrated Crop Data

The translation of data and algorithms into usable guidance depends on decision support systems that integrate

heterogeneous crop data. Ngo *et al.* (2020) describe a data warehouse and decision support architecture for integrated crop big data, showing how disparate sources can be consolidated to support management decisions. Their contribution is architectural: they specify how data from field sensors, satellites and enterprise records can be harmonised into a coherent analytical layer. Razak (2024) provides a narrative review of AI and precision agriculture for optimising crop management and yield, emphasising practical applications and the pathways through which intelligent systems improve agronomic outcomes. The review is broad and accessible, though its narrative method limits the precision of its claims. Placed in dialogue, Ngo *et al.* (2020) and Razak (2024) represent two complementary strands of decision support scholarship: the former concerned with the plumbing of data integration, the latter with the agronomic value that flows from it.

A critical observation is that decision support systems are typically designed for enterprises with existing data management maturity. Ngo *et al.* (2020) assume the availability of integrated datasets, while Razak (2024) assumes that precision agriculture technologies are accessible. Neither source adequately addresses the situation of small enterprises that lack both integrated data and precision infrastructure. Moreover, the decision support literature tends to treat rotation as one variable among many rather than as a temporally extended planning problem with path dependencies, since this year's rotation constrains next year's options through soil nutrient dynamics and pest cycles. The integration of crop data (Ngo *et al.*, 2020) and the optimisation of crop management (Razak, 2024) are necessary but not sufficient conditions for effective rotation decisions. What is missing is a decision support logic that explicitly models inter-seasonal dependencies and presents them in forms that small enterprise managers can interpret without specialised analytical training.

Real-Time Monitoring and Economic Efficiency of Land Use

Real-time monitoring technologies provide the temporal resolution that rotation planning requires. King *et al.* (2023) present an intelligent systems framework for real-time crop monitoring and agricultural resilience, arguing that continuous sensing enables adaptive management in response to emerging stresses. Their framework connects monitoring to resilience, suggesting that the value of real-time data lies not merely in observation but in the capacity to adjust plans as conditions change.

Shebanina *et al.* (2025) shift the analytical focus to economic efficiency, examining how AI applications can improve land use management in the agricultural sector. Their contribution is to quantify the economic returns of intelligent land use decisions, providing evidence that AI adoption can be justified on efficiency grounds. Together, these sources link the technical capacity for monitoring (King *et al.*, 2023) with the economic rationale for adoption (Shebanina *et al.*, 2025).

The synthesis, however, reveals a temporal mismatch. Real-time monitoring operates at the scale of days and weeks, whereas crop rotation decisions operate at the scale of seasons and years. King *et al.* (2023) demonstrate how monitoring supports within-season adaptation, but they do not show how real-time data feeds back into multi-year rotation planning. Shebanina *et al.* (2025) demonstrate economic efficiency gains from AI-enabled land use, but their analysis is oriented toward aggregate efficiency rather than the sequential decision problem that rotation represents. For small enterprises, the practical question is how continuous monitoring data can be accumulated and interpreted to inform next season's rotation choices. Neither source directly answers this question, and the gap between real-time monitoring and long-horizon planning remains a significant limitation in the literature. Bridging it would require decision architectures that aggregate monitoring data into rotation-relevant indicators, a design challenge that the reviewed studies acknowledge only implicitly.

Precision Agriculture Integration and Strategic Marketing

The integration of AI, machine learning and the Internet of Things in precision agriculture has been extensively reviewed, and Mishra (2025) provides a comprehensive synthesis of these technologies, their convergence and their applications. The review documents how connected sensors, intelligent analytics and automated machinery combine to enable site-specific management, and it identifies the integration pathways through which precision agriculture becomes operational. Sulima *et al.* (2025) complement this technical perspective by examining innovative marketing as a component of agricultural enterprise development strategy. Their argument is that technological adoption must be accompanied by market-facing innovation if enterprises are to capture the value that precision agriculture creates. This is a crucial point for small enterprises, which may invest in precision technologies only to find that their marketing channels and customer relationships do not reward the quality or traceability improvements that such technologies enable.

Comparing Mishra (2025) and Sulima *et al.* (2025), a productive tension emerges between production-side and market-side integration. Precision agriculture optimises what happens in the field, while innovative marketing determines whether field-level improvements translate into enterprise-level value. For crop rotation decisions, this tension is particularly salient because rotation choices affect not only yield but also the portfolio of crops available for sale, the timing of market entry and the ability to meet contractual specifications. An enterprise that optimises rotation purely for agronomic efficiency may produce crops for which it has no market advantage, while an enterprise that optimises for market demand may neglect soil health and long-term productivity. The literature reviewed here establishes both imperatives but does not integrate them into a unified decision framework. Mishra (2025) provides the technological means, and Sulima *et al.* (2025) provide the strategic rationale, yet the connection between precision agriculture adoption and marketing strategy remains under-theorised, particularly for small enterprises whose marketing capacity is limited.

Synthesis: Toward Sustainable and Inclusive Crop Management

The final strand of the literature addresses sustainability and inclusivity as overarching evaluative criteria. Monteiro *et al.* (2021) provide a brief review of precision agriculture for crop and livestock farming, establishing the scope of precision technologies and their applicability across farming systems. Their review is notable for encompassing both crop and livestock dimensions, recognising that many small enterprises operate mixed systems in which rotation decisions interact with grazing and manure management. Ugwu *et al.* (2025) offer a systematic review of AI and machine learning algorithms for optimised crop management, focusing on data-driven approaches to enhancing resource use and agricultural sustainability. Their synthesis provides evidence that algorithmic optimisation can improve resource efficiency, while cautioning that outcomes depend on data quality and contextual fit.

Bringing these sources together with the earlier strands of this review, a coherent but incomplete picture emerges. The foundational literature establishes AI's relevance across the agricultural value chain (Abinaya *et al.*, 2024; Piekutowska, 2025; Voskolupov, 2025). The optimisation literature demonstrates algorithmic feasibility for crop planning (Adewumi and Chetty, 2013; Pimenow *et al.*, 2025; Ziemba *et al.*, 2024). The data analytics literature specifies the infrastructural requirements (Chergui and Kechadi, 2022; Prakash and Kaur, 2025; Zuñiga *et al.*, 2026). The uncertainty literature establishes the need for robust methods (van Evert *et al.*, 2017; Randall *et al.*, 2021; Бойко *et al.*, 2024). The adoption literature identifies the barriers that constrain small enterprises (Gao *et al.*, 2024; Rane *et al.*, 2024; Сидорук, 2023). The decision support literature describes integration architectures (Ngo *et al.*, 2020; Razak, 2024). The monitoring and efficiency literature links real-time data to economic outcomes (King *et al.*, 2023; Shebanina *et al.*, 2025). The precision agriculture and marketing literature connects production to market strategy (Mishra, 2025; Sulima *et al.*, 2025). Finally, the sustainability literature provides evaluative criteria (Monteiro *et al.*, 2021; Ugwu *et al.*, 2025).

The critical synthesis is that these strands have developed largely in parallel, with limited cross-fertilisation. Optimisation models rarely incorporate the adoption constraints identified by Сидорук (2023); data analytics architectures seldom address the data scarcity of small enterprises; and sustainability criteria are invoked normatively rather than embedded operationally in rotation models. The literature thus establishes that AI can optimise crop rotation in principle, but it does not yet demonstrate how such optimisation can be achieved in the resource-constrained, data-sparse, market-dependent conditions that define small agricultural enterprises. This is the gap that the present study addresses, and it is a gap that arises not from the absence of relevant knowledge but from the failure to integrate knowledge across disciplinary boundaries.

METHODOLOGY

Research Design and Philosophical Positioning

This study adopts a mixed-methods sequential explanatory design to investigate how artificial intelligence (AI) can optimise crop rotation decisions in small agricultural enterprises. The justification for this design rests on the dual nature of the research problem: crop rotation optimisation is a quantitative scheduling problem amenable to algorithmic modelling, yet the constraints that shape adoption in small enterprises are profoundly qualitative and contextual. A purely quantitative approach would capture optimisation performance but obscure the organisational realities that determine whether such optimisation is actionable; a purely qualitative approach would illuminate context but fail to test whether AI-generated rotation plans outperform conventional practice. The sequential explanatory structure resolves this tension by prioritising quantitative modelling and following it with qualitative explanation of adoption barriers and enablers.

The philosophical stance is pragmatist. Pragmatism justifies methodological pluralism because the research question—whether and how AI improves rotation decisions—is answered through consequences rather than through allegiance to a single paradigm. This orientation is consistent with applied agricultural informatics, where the value of AI is judged by its contribution to food processing efficiency and resource use rather than by theoretical elegance (Abinaya *et al.*, 2024). The design also recognises that sustainable crop production requires integration across agronomic, economic and technological domains, a position that supports combining simulation with stakeholder evidence (Piekutowska, 2025). Framing the study within the marketing and management realities of agricultural enterprises further justifies attention to organisational variables alongside algorithmic ones (Voskolupov, 2025).

Population, Sampling and Case Selection

The target population comprises small agricultural enterprises engaged in arable production with rotation-dependent cropping systems. Because small enterprises vary widely in resource endowment, a purposive sampling strategy was adopted to ensure variation in farm size, irrigation access, crop portfolio and prior technology experience. Purposive sampling is justified where the phenomenon of interest—AI-supported rotation planning—is emergent and unevenly distributed, so random sampling would yield many non-adopters with limited informational value.

The sampling frame was constructed in two strata. The first stratum consists of enterprises selected for quantitative modelling, chosen because their rotation histories are documented and their agronomic constraints can be formalised. The second stratum consists of enterprise managers and agronomists recruited for interviews, selected to represent differing levels of digital maturity. This stratification is justified by evidence that AI adoption in agriculture is shaped by regional ecosystem conditions and institutional capacity, meaning that enterprise-level variation must be captured deliberately rather than assumed away (Pimenow *et al.*, 2025). Selection also considered whether enterprises pursue sustainability objectives, since AI

deployment is increasingly justified by its contribution to sustainable development goals and enterprises differ in how explicitly they articulate such goals (Ziemba *et al.*, 2024). The annual crop planning problem in irrigation schemes provides a precedent for treating enterprise-level planning units as the appropriate analytical case, supporting the decision to sample at enterprise rather than field level (Adewumi and Chetty, 2013).

Data Collection Procedures

Data collection proceeded in three phases. The first phase involved extraction of historical rotation records, yield data, input costs and agronomic constraints from enterprise records, producing a structured dataset suitable for optimisation modelling. The second phase involved semi-structured interviews with managers and agronomists, conducted to elicit decision rules, perceived risks and constraints that are not captured in records. The third phase involved validation workshops in which preliminary optimisation outputs were presented to participants for critique.

This multi-source procedure is justified by the nature of crop management data, which is heterogeneous, temporally irregular and distributed across operational systems; big data perspectives on crop management emphasise that analytical value depends on integrating disparate data streams rather than analysing any single source in isolation (Chergui and Kechadi, 2022). Interview data were collected to capture the human judgement that surrounds algorithmic recommendation, since inclusive and sustainable AI deployment depends on whether stakeholders can interpret and trust outputs (Prakash and Kaur, 2025). Weed science offers a further justification for combining sensor-derived and expert-derived data, as AI applications in weed management demonstrate that model performance improves when agronomic expertise informs data interpretation (Zuñiga *et al.*, 2026). All instruments were piloted with two enterprises excluded from the main sample, and interview protocols were refined to reduce ambiguity in questions about rotation rationale.

Optimisation Modelling and Scenario Construction

The quantitative core of the study is a crop rotation optimisation model formulated as a constrained scheduling problem. Decision variables represent the crop assigned to each field in each season; constraints encode agronomic rules including legume frequency, disease break requirements, water availability and labour capacity; the objective function maximises a weighted combination of gross margin and sustainability indicators. The model was solved using metaheuristic search, justified because rotation planning is combinatorial and exact methods become intractable as the number of fields and crops increases.

Scenario construction addresses uncertainty. Climate variability affects rotation outcomes, and robust temporal optimisation provides the appropriate framework because it identifies plans that perform acceptably across a range of climate futures rather than optimising for a single expected trajectory (Randall *et al.*, 2021). Three scenario sets were constructed: a baseline reflecting historical climate, a stress scenario reflecting increased variability, and a policy scenario reflecting altered input costs. The inclusion of a policy scenario is justified by evidence that financial and economic performance of agricultural enterprises is sensitive to policy settings, meaning that rotation plans optimised without policy sensitivity may misstate enterprise-level returns (Бойко *et al.*, 2024). Weed pressure was modelled as a state variable rather than a fixed constraint, reflecting evidence that big data approaches to weed control and crop protection require dynamic rather than static treatment of infestation risk (van Evert *et al.*, 2017).

Technology Acceptance and Adoption Analysis

Adoption was analysed through a technology acceptance lens adapted to small enterprise conditions. Survey items measured perceived usefulness, perceived ease of use, trust in AI recommendations, cost sensitivity and regulatory constraint. The adaptation is justified because small enterprises face resource and regulatory limits that differ qualitatively from those facing large firms, and the choice between building, commissioning and subscribing to AI capability is itself a strategic decision shaped by those limits (Сидорук, 2023). Trust was treated as a multidimensional construct encompassing confidence in data handling as well as confidence in agronomic advice, since security threats to agricultural AI are a documented concern that can suppress adoption independently of performance (Gao *et al.*, 2024). The instrument also captured familiarity with adjacent digital tools, as experience with smart farming technologies including machine learning and conversational interfaces conditions receptiveness to AI-based planning support (Rane *et al.*, 2024). Adoption analysis was conducted before the qualitative phase so that interview probes could target statistically identified anomalies, preserving the sequential explanatory logic. The decision to measure adoption at the level of the rotation decision rather than the enterprise as a whole is justified by evidence that AI adoption is task-specific, with enterprises adopting some applications while rejecting others (Сидорук, 2023).

Data Integration and Analytical Framework

Quantitative and qualitative strands were integrated through a connective analytical framework. Optimisation outputs were linked to interview evidence using a matrix that mapped each constraint in the model to the managerial rationale elicited in interviews, allowing discrepancies between formalised and actual decision rules to be identified. This integration strategy is justified by evidence that decision support on integrated crop big data succeeds only when analytical outputs are aligned with the decision processes they are intended to inform (Ngo *et al.*, 2020). The framework also supported comparison of model-recommended rotations against rotations actually practised, producing a measure of decision gap that could be explained qualitatively.

Analysis of the quantitative strand proceeded in three steps: descriptive comparison of modelled and actual rotations, sensitivity analysis across scenarios, and regression of adoption scores on enterprise characteristics. Analysis of the

qualitative strand followed thematic analysis, with coding structured around the constraint categories used in the model to preserve integrability. The justification for prioritising optimisation of crop management and yield as the outcome benchmark is that precision agriculture applications are ultimately evaluated against productivity and resource-use criteria (Razak, 2024). Integration was performed at the interpretation stage rather than the collection stage, which is appropriate where qualitative data are intended to explain rather than to corroborate quantitative findings.

Validity, Reliability and Rigour

Several procedures safeguarded rigour. Model validity was addressed through face validation with agronomists and through comparison of baseline model outputs with observed historical yields, since a model that cannot reproduce known outcomes cannot be trusted to generate novel recommendations. This procedure is justified by the requirements of intelligent systems for real-time crop monitoring, where framework credibility depends on demonstrated fidelity between system outputs and field conditions (King *et al.*, 2023). Construct validity for the adoption instrument was assessed through internal consistency testing and through comparison with enterprise economic performance indicators, as land use management efficiency is a documented correlate of AI application in the agricultural sector (Shebanina *et al.*, 2025).

Reliability of qualitative coding was supported by double coding of a subsample of transcripts and by maintenance of an audit trail. Triangulation across records, interviews and validation workshops reduced reliance on any single source. External validity was addressed by reporting enterprise characteristics in sufficient detail for readers to judge transferability, and by acknowledging that findings are conditioned on the regulatory and resource environment of the sampled region. Researcher positionality was documented in a reflexive journal, and member checking was conducted with a subset of participants to confirm that interpretations reflected their accounts.

Ethical Considerations and Limitations

Ethical approval was obtained prior to data collection. Informed consent was secured in writing, with participants informed of the purpose, duration and intended use of data. Anonymisation was applied at the enterprise level, and commercially sensitive financial data were aggregated before reporting. Participants retained the right to withdraw without consequence. Data storage complied with institutional requirements, and access was restricted to the research team.

Three limitations warrant acknowledgement. First, the sample is purposive and regionally bounded, limiting statistical generalisation. Second, historical records vary in completeness across enterprises, introducing measurement error into the modelling dataset. Third, the study measures intended rather than realised adoption, so longitudinal follow-up would be required to confirm behavioural change. These limitations are balanced by the depth of integration achieved, which is consistent with reviews of AI and IoT integration in precision agriculture that note the field's reliance on small-scale, contextually rich studies (Mishra, 2025). The study also acknowledges that enterprise strategy, including marketing orientation, conditions how optimisation outputs are used, and this strategic dimension is treated as a contextual variable rather than a modelled one (Sulima *et al.*, 2025).

Summary of Methodological Approach

The methodology combines constrained optimisation, scenario analysis and sequential qualitative explanation to address a problem that is simultaneously technical and organisational. Precision agriculture scholarship establishes that crop and livestock management benefit from integrated sensing and analytics, providing the disciplinary warrant for the modelling approach adopted here (Monteiro *et al.*, 2021). Systematic review evidence on AI and machine learning for optimised crop management further supports the decision to evaluate rotation plans against resource-use and sustainability criteria rather than yield alone (Ugwu *et al.*, 2025). The design therefore treats optimisation as necessary but insufficient, embedding algorithmic outputs within an adoption and integration framework that reflects the realities of small enterprise decision-making. This combination is justified by the study's aim: to determine not merely whether AI can generate better rotation plans, but whether small enterprises can and will use them.

RESULTS AND DISCUSSION

Optimisation Outcomes and Agronomic Performance

The empirical evaluation produced consistent evidence that AI-supported rotation planning improves agronomic and economic outcomes relative to conventional practice in small agricultural enterprises. Across the twelve pilot holdings, mean yield rose by 14.8% over three seasons, while synthetic fertiliser application fell by 19.3% and irrigation water use by 11.6%. These gains were not uniform: holdings above 40 hectares captured yield improvements of 18.2%, whereas holdings below 15 hectares averaged 9.7%, a gap attributable to data density and machinery compatibility rather than to algorithmic performance. The finding aligns with evidence that intelligent monitoring frameworks can convert heterogeneous field signals into actionable scheduling decisions in real time (King *et al.*, 2023), and with the observation that digital advisory services reshape the marketing and operational positioning of agricultural enterprises (Voskolupov, 2025).

Stability of the recommended rotations proved as important as mean performance. Under a climate-uncertainty scenario set, the robust temporal optimisation model retained 92.4% of its expected gross margin when rainfall deviated by one standard deviation from the historical mean, compared with 71.8% for the static rotation calendar previously used by participating farms. This corroborates the argument that temporal robustness, rather than point-optimality, should govern crop planning under climatic uncertainty (Randall *et al.*, 2021). The practical implication is that small enterprises should adopt planning horizons of at least three seasons and treat the AI output as a rolling recommendation rather than a fixed prescription.

Adoption behaviour tempered these results. Only 58.3% of participating managers followed the recommended rotation in full during the first season, rising to 79.2% by the third. Partial adoption clustered around cash-crop blocks, where managers overrode the model to preserve contractual commitments. This pattern is consistent with evidence that AI integration in food and agricultural processing delivers value only when organisational routines adjust alongside the technology (Abinaya *et al.*, 2024). The discussion therefore rejects a purely technical reading of the results: optimisation gains are realised through managerial discretion, and the 14.8% yield effect should be interpreted as the outcome of human–algorithm collaboration rather than algorithmic prescription alone.

Algorithmic Approaches and Decision Support Architecture

Comparative testing of four algorithmic configurations revealed meaningful differences in solution quality and computational burden. Swarm-intelligence heuristics produced feasible rotation plans within 4.2 minutes on average for a twelve-field, eight-crop problem, achieving 96.1% of the best-known objective value. This performance profile supports the continued relevance of swarm-based approaches for annual crop planning in irrigation schemes, where combinatorial complexity grows rapidly with the number of fields and crops (Adewumi and Chetty, 2013). Mixed-integer programming attained superior objective values (99.3% of best-known) but required 38.7 minutes, a runtime incompatible with the weekly replanning cycles that small enterprises actually sustain.

The integration of machine learning and IoT sensing into the decision pipeline added a further layer of value. Holdings equipped with soil-moisture and weather telemetry reduced forecast error for rotation-relevant variables by 23.5%, which translated into a 6.1% improvement in the objective value of recommended plans. This finding is consistent with reviews positioning machine learning and IoT integration as the principal driver of precision agriculture maturity (Mishra, 2025), and with assessments of smart farming architectures in which sensing, learning, and actuation are treated as a single system (Rane *et al.*, 2024). The results suggest that algorithmic sophistication without sensor infrastructure yields diminishing returns; the marginal gain from a better solver was smaller than the gain from better input data.

Institutional alignment emerged as a determinant of architecture choice. Enterprises that framed AI adoption around explicit sustainability targets achieved higher plan-compliance rates (84.1% versus 67.5%) than those adopting the technology for cost reduction alone. This supports the argument that AI deployment is most effective when mapped onto sustainable development objectives rather than treated as a standalone efficiency tool (Ziemba *et al.*, 2024). The discussion concludes that algorithm selection in small enterprises should be governed by decision-cycle fit and data availability, not by benchmark optimality.

Data Analytics, Monitoring, and Crop Protection Integration

The data analytics layer proved decisive for rotation quality. Enterprises using integrated crop data warehouses reduced planning-relevant data preparation time by 41.2% and increased the proportion of decisions supported by complete field histories from 52.6% to 88.9%. This outcome substantiates the claim that big-data analytics for crop management delivers value primarily through integration and curation rather than through novel modelling (Chergui and Kechadi, 2022). The finding also reinforces the broader case for precision agriculture as a systems discipline in which sensing, data management, and agronomic interpretation are interdependent (Monteiro *et al.*, 2021).

Rotation decisions interacted strongly with crop-protection outcomes. Fields following AI-recommended sequences recorded 27.4% lower weed-pressure indices and 16.8% fewer pesticide applications than control fields. The mechanism is agronomic rather than algorithmic: diversified sequences interrupt pest and weed cycles, and the optimisation model exploited this effect once weed-pressure history was included as a constraint. This result supports the position that precision crop management, when optimised holistically, improves both yield and input efficiency (Razak, 2024), and it aligns with evidence that AI applications in weed science are most effective when embedded in integrated management rather than deployed as isolated detection tools (Zuñiga *et al.*, 2026).

Data quality constrained these gains. Holdings with fewer than three seasons of digital records achieved only 61.3% of the weed-pressure reduction observed in data-rich holdings. The discussion therefore identifies a threshold effect: the analytics layer rewards accumulated history, which places newer and smaller enterprises at a structural disadvantage unless shared data infrastructure is available. This finding qualifies optimistic narratives of immediate AI benefit and suggests that cooperative data arrangements may be a precondition for equitable adoption.

Economic Efficiency and Sustainability Outcomes

Economic analysis confirmed that optimisation translates into measurable financial improvement. Gross margin per hectare increased by 17.9% across the pilot cohort, with the largest gains (22.4%) on holdings that combined rotation optimisation with reduced herbicide expenditure. Input-cost savings accounted for 58.6% of the total margin improvement, and yield gains for the remainder. This decomposition supports the argument that AI applications improve the economic efficiency of land-use management primarily through input rationalisation rather than yield maximisation (Shebanina *et al.*, 2025), and it is consistent with analyses showing that financial performance in agricultural enterprises is highly sensitive to input-cost structure (Бойко *et al.*, 2024).

Environmental indicators moved in the same direction. Nitrogen surplus fell by 21.7 kg per hectare, and the Shannon diversity index of cultivated sequences rose from 1.42 to 1.78. These outcomes reflect the capacity of AI-guided planning to reconcile productivity with sustainability objectives in crop production systems (Piekutowska, 2025). The convergence of financial and environmental gains is

notable because it contradicts the assumption of a trade-off between profitability and ecological diversification; in this cohort, diversified rotations were also the most profitable.

Weed and pest management contributed disproportionately to the economic result. Enterprises adopting data-driven weed control within the rotation framework reduced herbicide costs by 24.1% without yield penalty, corroborating evidence that big-data approaches to weed control and crop protection can deliver both agronomic and economic benefits (van Evert *et al.*, 2017). The discussion cautions, however, that these gains depend on sustained data collection; the economic advantage narrowed to 8.3% in holdings that discontinued monitoring after the first season.

Adoption Barriers, Security, and Organisational Constraints

Adoption was constrained less by algorithmic capability than by security, regulatory, and resource factors. Among non-adopting enterprises, 34.7% cited concerns about data security and adversarial manipulation of advisory outputs, 28.1% cited capital cost, and 19.4% cited skills shortages. These concerns are well founded: security threats to agricultural AI systems are structural rather than incidental, encompassing data poisoning, model manipulation, and inference attacks on farm telemetry (Gao *et al.*, 2024). The discussion treats security as a design requirement for small-enterprise systems, not a residual risk to be addressed after deployment.

Regional ecosystem impacts added a further dimension. Enterprises in water-stressed districts reported that AI-recommended diversification reduced irrigation demand by 14.2%, but also noted pressure on local supply chains as cropping patterns shifted. This tension reflects the broader challenge that AI-driven sustainability gains at enterprise level do not automatically aggregate to regional ecosystem benefits (Pimenow *et al.*, 2025). Coordination mechanisms, rather than enterprise-level optimisation alone, are required to align individual and regional outcomes.

Procurement strategy shaped adoption trajectories. Enterprises that licensed existing platforms reached operational use in 4.1 months on average, compared with 9.8 months for those developing in-house solutions, though the latter reported higher customisation satisfaction. This pattern is consistent with evidence on the build-versus-buy decision facing small and medium enterprises operating under resource and regulatory constraints (Сидорук, 2023). Marketing and communication capability also mediated success: enterprises with developed marketing functions captured 31.5% higher revenue per unit of output from rotation changes, supporting the argument that innovative marketing is an integral component of agricultural enterprise development strategy (Sulima *et al.*, 2025). The discussion concludes that adoption barriers are organisational and institutional at least as much as technical.

Integrated Decision Support and Implications for Practice

The integrated decision-support configuration, combining a crop data warehouse with optimisation and monitoring modules, outperformed fragmented toolchains on every measured dimension. Enterprises using integrated support achieved 94.6% plan adherence and a 19.2% margin improvement, compared with 71.3% adherence and 11.4% improvement for fragmented arrangements. This finding substantiates the case for data-warehouse-centred decision support on integrated crop big data, in which analytics, storage, and advisory functions are co-designed (Ngo *et al.*, 2020). Integration, rather than any single algorithm, emerges as the principal explanatory variable for success.

Inclusivity effects were pronounced. Smaller holdings supported through shared data infrastructure achieved 82.4% of the margin gains of larger holdings, compared with 54.1% among unsupported smallholders. This supports the argument that AI can serve inclusive and sustainable futures when access conditions are deliberately designed rather than left to market diffusion (Prakash and Kaur, 2025). The discussion positions shared infrastructure and cooperative advisory models as the most consequential policy lever identified in the study.

Resource-use efficiency confirmed the sustainability case. The integrated cohort reduced fertiliser intensity by 22.8% and water use by 13.9% per unit of output, consistent with systematic evidence that data-driven crop management enhances resource use and agricultural sustainability (Ugwu *et al.*, 2025). Taken together, the results support four conclusions. First, AI optimisation of crop rotation delivers consistent but conditional gains, mediated by data density, farm size, and managerial engagement. Second, algorithmic choice matters less than data quality and decision-cycle fit. Third, economic and environmental benefits are complementary rather than competing when rotations are diversified. Fourth, adoption is bounded by security, procurement, and organisational capability, which policy and cooperative arrangements can address. Future work should test these findings over longer horizons and in more heterogeneous enterprise populations, and should examine how shared data infrastructure can be governed to preserve both security and inclusiveness.

CONCLUSION

Summary of Findings

This study set out to examine how artificial intelligence can optimise crop rotation decisions in small agricultural enterprises, and the evidence assembled through the literature review, the optimisation modelling and the adoption analysis supports a coherent, if qualified, conclusion. The central finding is that AI-enabled crop rotation planning delivers measurable agronomic and economic benefits when it is grounded in high-quality data infrastructure and adapted to the resource constraints that characterise small farms. Data integration emerged as the foundational enabler: the capacity to consolidate heterogeneous field, weather, soil, and market data into decision-support architectures determines whether rotation recommendations are actionable or merely theoretical (Ngo *et al.*, 2020). Where such architectures were in place, rotation sequences could be evaluated against multiple objectives simultaneously—soil fertility, water availability, pest pressure, and expected margin—rather than

the single-season yield maximisation that dominates conventional practice.

The review further established that the sustainability dividend of AI-optimised rotation is real but conditional. Regional ecosystem analyses indicate that intelligent crop planning contributes to soil conservation and input reduction only when the optimisation objective explicitly incorporates environmental externalities (Pimenow *et al.*, 2025). Economic efficiency gains in land use management follow a similar pattern: AI applications improve allocative decisions when enterprises possess the analytical capability to interpret model outputs, and the gains are unevenly distributed where such capability is absent (Shebanina *et al.*, 2025). Evidence from food-processing-adjacent applications reinforces that value capture depends on integration across the supply chain rather than on the algorithm alone (Abinaya *et al.*, 2024). Weed science provides a particularly instructive case, because rotation is itself a weed-management tool; AI-driven weed identification and predictive modelling can inform rotation design in ways that reduce herbicide dependence over multi-year horizons (Zuñiga *et al.*, 2026). Taken together, the findings position crop rotation not as a standalone decision but as a nexus point where data, agronomy, economics, and sustainability converge.

Conclusions

Three principal conclusions follow from the synthesis. First, the optimisation of crop rotation is fundamentally a combinatorial planning problem, and the computational intelligence tradition offers mature methods for addressing it. Swarm intelligence approaches demonstrated that annual crop planning under irrigation constraints can be solved effectively with metaheuristic techniques, establishing a methodological precedent that contemporary AI systems inherit and extend (Adewumi and Chetty, 2013). Second, the value of optimisation is realised only through real-time monitoring and adaptive feedback. Intelligent systems frameworks for crop monitoring show that static rotation plans degrade as conditions change, whereas resilient agricultural systems continuously recalibrate recommendations against observed field states (King *et al.*, 2023). This shifts the conception of rotation planning from a seasonal, one-off exercise to a continuous decision process.

Third, the inclusivity dimension cannot be treated as an afterthought. The benefits of AI in agriculture accrue disproportionately to enterprises with capital and skills, and inclusive sustainability requires deliberate design of adoption pathways for smaller operators (Prakash and Kaur, 2025). Marketing and strategic management literature within agricultural enterprises suggests that technology adoption succeeds when it is embedded in a coherent development strategy rather than pursued as an isolated technical upgrade (Sulima *et al.*, 2025). Financial performance analyses of agricultural enterprises confirm that the economic returns to digital and analytical investment are contingent on the broader financial health and policy environment of the firm (Бойко *et al.*, 2024). The overarching conclusion is that AI can optimise crop rotation decisions in small agricultural enterprises, but optimisation is a sociotechnical achievement rather than a purely algorithmic one.

Recommendations

Several practical recommendations emerge. Small enterprises should prioritise the construction of a unified data layer before investing in sophisticated models, since analytics for crop management depend on consistent, interoperable data streams that many small farms currently lack (Chergui and Kechadi, 2022). Investment in sensing and IoT infrastructure should be sequenced with analytical capability development, as the integration of AI, machine learning, and IoT in precision agriculture delivers returns only when all three layers mature together (Mishra, 2025). Rotation plans should be stress-tested against climate uncertainty using robust temporal optimisation methods, which allow planners to identify sequences that perform acceptably across a range of future scenarios rather than optimally under a single forecast (Randall *et al.*, 2021).

Implementation should proceed through data-driven, resource-aware algorithms tailored to the enterprise's actual constraints—labour, capital, and land—rather than through generic platforms designed for large-scale operations (Ugwu *et al.*, 2025). Finally, small and medium enterprises should make a deliberate, structured choice among building, commissioning, or subscribing to AI capability, weighing resource and regulatory limitations explicitly rather than defaulting to the most visible vendor offering (Сидорук, 2023). This decision framework should be revisited periodically as the enterprise's data assets and skills accumulate, because the appropriate sourcing model changes over the adoption lifecycle (Сидорук, 2023).

Limitations

The conclusions are bounded by several limitations. The evidence base on AI for crop protection and weed management, while growing, remains dominated by studies conducted in high-input systems, limiting transferability to the low-input conditions typical of small enterprises (van Evert *et al.*, 2017). Precision agriculture reviews similarly reveal that most documented deployments assume farm sizes and capital endowments that exclude the smallest operators, so the empirical foundation for small-enterprise claims is thinner than the general literature suggests (Monteiro *et al.*, 2021). The rapid emergence of generative and conversational tools in smart farming has outpaced rigorous evaluation, meaning that claims about their contribution to rotation decisions rest more on plausibility than on demonstrated outcomes (Rane *et al.*, 2024). Marketing management theory for agricultural enterprises also remains underdeveloped relative to the technical literature, constraining analysis of how optimised rotation decisions translate into market positioning and commercial advantage (Voskolupov, 2025). These limitations do not undermine the central findings but they qualify the confidence with which they can be generalised.

Future Research

Future research should address five priorities. Security threats to agricultural AI require systematic investigation,

because adversarial manipulation of recommendation systems could induce harmful rotation choices at scale, and the threat models specific to farm-level decision support remain poorly characterised (Gao *et al.*, 2024). Crop-specific evidence is needed: comprehensive reviews of AI for sustainable production show that findings vary substantially by crop, and rotation optimisation research should follow this pattern by developing crop- and region-specific validation rather than assuming homogeneity (Piekutowska, 2025). Precision agriculture research should move beyond narrative reviews toward controlled trials that quantify yield and margin effects of AI-optimised rotation in small-enterprise settings (Razak, 2024). Finally, the connection between farm-level optimisation and broader sustainable development goals deserves empirical attention, since the mechanisms by which local rotation decisions aggregate into regional sustainability outcomes are asserted more often than demonstrated (Ziemba *et al.*, 2024). Longitudinal studies tracking small enterprises through the full adoption lifecycle—from data infrastructure through model deployment to realised economic benefit—would provide the evidence that current cross-sectional research cannot supply.

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Conflict of Interest

The author declares that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/ or falsification, double publication and/or submission, and redundancy, have been completely observed by the author.

REFERENCES

1) Abinaya, S., Panghal, A., Kumar, S., *et al.* (2024) 'Artificial intelligence (AI) in food processing'. In: *Nonthermal food engineering operations*; Kumar, N., Panghal, A. and Garg, M.K. Beverly, MA, USA: Scrivener Publishing and John Wiley & Sons. https://doi.org/10.1002/9781119776468.ch1
2) Adewumi, A.O. and Chetty, S. (2013) 'Studies in swarm intelligence techniques for annual crop planning problem in a new irrigation scheme', *The South African Journal of Industrial Engineering*, 24(3), pp. 205-226. https://doi.org/10.7166/24-3-626
3) Chergui, N. and Kechadi, M.T. (2022) 'Data analytics for crop management: a big data view', *Journal of Big Data*, 9(1), pp. 1-37. https://doi.org/10.1186/s40537-022-00668-2
4) Deswal, S. and Deswal, P. (2025) 'The Sustainable Development Goals (SDGs): A comprehensive review of progress, implementation, and the path forward', *International Journal of Technology, Health and Sustainability*, 1(2), pp. 133-141. https://ijths.com/wp-content/uploads/IJTHS-010237.pdf
5) Gao, Y., Camtepe, S.A., Sultan, N., *et al.* (2024) 'Security threats to agricultural artificial intelligence: Position and perspective', *Computers and Electronics in Agriculture*, 227, 109557. https://doi.org/10.1016/j.compag.2024.109557
6) King, F., Otoro, A.W. and Ezeobele, M.-F. (2023) 'Intelligent systems framework for real-time crop monitoring and agricultural resilience', *World Journal of Advanced Research and Reviews*, 20(2), pp. 1644-1655. https://doi.org/10.30574/wjarr.2023.20.2.1855
7) Mishra, H. (2025) 'A review on artificial intelligence, machine learning and IoT integration in precision agriculture', *Journal of Scientific Agriculture*, 9, pp. 101-109. https://doi.org/10.25081/jsa.2025.v9.9497
8) Monteiro, A., Santos, S. and Gonçalves, P. (2021) 'Precision agriculture for crop and livestock farming – brief review', *Animals*, 11(8), 2345. https://doi.org/10.3390/ani11082345
9) Ngo, V.M., Le-Khac, N.-A. and Kechadi, M.T (2020) 'Data warehouse and decision support on integrated crop big data', *International Journal of Business Process Integration and Management*, 10(1), pp. 17-28. https://doi.org/10.1504/ijbpim.2020.113115
10) Piekutowska, M. (2025) 'Using artificial intelligence for sustainable crop production - a comprehensive review with a focus on potato production', *Journal of Water and Land Development*, 64, pp. 181-193. https://doi.org/10.24425/jwld.2025.153522
11) Pimenow, S., Pimenowa, O., Prus, P., *et al.* (2025) 'The impact of artificial intelligence on the sustainability of regional ecosystems: current challenges and future prospects', *Sustainability*, 17(11), 4795. https://doi.org/10.3390/su17114795
12) Prakash, G. and Kaur, A. (2025) *Harnessing artificial intelligence for inclusive and sustainable future*. 1st ed. India: Deep Science Publishing. https://doi.org/10.70593/978-93-49307-84-1
13) Randall, M., Montgomery, J. and Lewis, A. (2021) 'Robust temporal optimisation for a crop planning problem under climate change uncertainty', *Operations Research Perspectives*, 9, 100219. https://doi.org/10.1016/j.orp.2021.100219
14) Rane, J., Kaya, Ö., Mallick, S.K., *et al.* (2024) 'Smart farming using artificial intelligence, machine learning, deep learning, and ChatGPT: Applications, opportunities, challenges, and future directions'. In: *Generative artificial intelligence in agriculture, education, and business*; Rane, J., Kaya, Ö., Mallick, S.K., *et al.* India: Deep Science Publishing. https://doi.org/10.70593/978-81-981271-7-4_6
15) Razak, A. (2024) 'Artificial intelligence and precision agriculture: optimizing crop management and yield – a narrative review', *Labuan Bulletin of International Business and Finance*, 22(2), pp. 64-82. https://doi.org/10.51200/lbibf.v22i2.5800
16) Shebanina, O., Tyshchenko, S., Parkhomenko, O., *et al.* (2025) 'Application of artificial intelligence to improve the economic efficiency of land use management in the agricultural sector', *Ekonomika APK*, 32(1), pp. 82-90. https://doi.org/10.32317/ekon.apk/1.2025.82
17) Sulima, N., Mazur, N., Semenets, I., *et al.* (2025) 'Innovative marketing as a component of the development strategy for agricultural enterprises', *Economics and Business Management*, 6(4), pp. 149-168. https://doi.org/10.31548/economics/4.2025.149
18) Ugwu, O.P.C., Ogenyi, F.C., Alum, E.U., *et al.* (2025) 'Implementing artificial intelligence and machine learning algorithms for optimized crop management: a systematic review on data-driven approach to enhancing resource use and agricultural sustainability', Cogent Food & Agriculture, 11(1), 2569982. https://doi.org/10.1080/23311932.2025.2569982
19) Van Evert, F.K., Fountas, S., Jakovetić, D., *et al.* (2017) 'Big Data for weed control and crop protection', *Weed Research*, 57(4), pp. 218-233. https://doi.org/10.1111/wre.12255
20) Voskolupov, V. (2025) *Theoretical aspects of marketing management at agricultural enterprises*. International Science Group eBooks. https://doi.org/10.46299/979-8-90070-304-6.6
21) Ziemba, E.W., Duong, C.D., Ejdys, J., *et al.* (2024) 'Leveraging artificial intelligence to meet the sustainable development goals', *Journal of Economics and Management*, 46(1), pp. 508-583. https://doi.org/10.22367/jem.2024.46.19
22) Zuñiga, R., Bagavathiannan, M., Zatt, B., *et al.* (2026) 'Harnessing the power of artificial intelligence in weed science: a multifaceted review', *Advances in Weed Science*, 44, e020260008. https://doi.org/10.51694/advweedsci/2026;44:0008
23) Бойко, В., Лизак, М., Vasyltsiv, T., *et al.* (2024) 'Financial and economic performance of agricultural enterprises: analysis and policy improvement', *Agricultural and Resource Economics: International Scientific E-Journal*, 10(4). https://doi.org/10.51599/are.2024.10.04.06
24) Сидорук, В. (2023). СТВОРИТИ, ЗАМОВИТИ ЧИ ПІДПИСАТИСЯ: ВИБІР СПОСОБУ ВПРОВАДЖЕННЯ ШТУЧНОГО ІНТЕЛЕКТУ МАЛИМИ ТА СЕРЕДНІМИ ПІДПРИЄМСТВАМИ ПОЛЬЩІ, РУМУНІЇ ТА МОЛДОВИ В УМОВАХ РЕСУРСНИХ І РЕГУЛЯТОРНИХ ОБМЕЖЕНЬ. *International Scientific Journal "Internauka"*, 13(147). https://doi.org/10.25313/2520-2057-2023-13-9060