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Artificial Intelligence for Sustainable Agriculture: A Systematic Literature Review of Applications, Resource Optimization, and Sustainability Outcomes

Try Koryati[1]*, Jongkers Tampubolon[2], Ika Rosenta Purba[3], Basyaruddin Basyaruddin[4], Muhammad Rizwan[5], Corry Corry[6], Nurhayati Nurhayati[7]

[1]Department of Agrotechnology, Universitas Amir Hamzah, Indonesia
[2]Department of Agribusiness, Universitas HKBP Nommensen, Indonesia
[3]Department of Urban and Regional Planning, Postgraduate Program, Universitas Simalungun, Indonesia
[4,5,7]Department of Agrotechnology, Universitas Islam Sumatera Utara, Indonesia
[6]Department of Magister Social Science Education, Universitas Simalungun, Indonesia
*Corresponding author's email: trykoryati@unhamzah.ac.id

ABSTRACT: Artificial Intelligence (AI) has increasingly emerged as an important technology for supporting sustainable agricultural practices and improving the efficiency of agricultural resource management. This systematic literature review examines the role of AI in sustainable agriculture, focusing on its major applications, contributions to resource optimization, and reported sustainability outcomes. The review analysed literature published between 2020 and 2025 using a systematic review approach guided by the PRISMA 2020 framework. The analysis focused on three interconnected dimensions: AI applications in agricultural production and management, optimization of agricultural resources, and environmental, agricultural, and economic sustainability outcomes. The findings indicate that AI is widely applied to crop monitoring, yield prediction, disease and pest detection, smart irrigation, soil and nutrient management, precision farming, and agricultural automation. The synthesis further shows that AI can support more efficient use of water, fertilizers, pesticides, energy, labor, and other agricultural inputs by enabling data-driven prediction and decision-making. These improvements are associated with potential gains in agricultural productivity, resource efficiency, environmental protection, and economic performance. However, the sustainability benefits of AI remain influenced by data quality, implementation costs, digital infrastructure, technical skills, model interpretability, and unequal access to technology. Overall, the review identifies a pathway in which AI applications support data-driven decisions, resource optimization, agricultural efficiency, and ultimately sustainability outcomes. Future research should therefore emphasize practical implementation, accessibility, cost-effectiveness, responsible AI, and long-term sustainability impacts, particularly in diverse agricultural and smallholder farming contexts.

INTRODUCTION

Agriculture is increasingly confronted with the need to produce sufficient food while responding to environmental degradation, climate variability, resource scarcity, and growing pressure on agricultural land and water. Conventional intensification strategies have contributed substantially to agricultural productivity, but they may also increase pressure on soil, water, energy, and agrochemical resources. Consequently, sustainable agriculture requires approaches that can simultaneously maintain or improve productivity while reducing unnecessary resource use and environmental impacts. Recent research emphasizes that agricultural sustainability increasingly depends on more precise and context-sensitive management of soil, water, nutrients, crops, and other production resources.

The emergence of digital technologies has created new opportunities to address these challenges through data-driven agricultural management. Among these technologies, artificial intelligence (AI) has attracted particular attention because of its ability to process large and heterogeneous datasets, identify patterns, generate predictions, and support complex agricultural decisions. Machine learning, deep learning, computer vision, and related AI techniques have increasingly been applied to crop monitoring, disease and pest detection, yield prediction, soil assessment, irrigation management, and precision farming. Ali et al. (2025) emphasize that AI-driven technologies are becoming increasingly relevant to sustainable crop production through applications involving monitoring, prediction, and intelligent agricultural management.

One of the most important contributions of AI to sustainable agriculture is its potential to improve resource optimization. Agricultural resources are not uniformly distributed across fields or production periods; therefore, applying the same amount of water, fertilizer, pesticide, or other inputs to every location may result in inefficient resource use. AI can support site-specific management by combining information from sensors, remote sensing, weather observations, historical production data, and other agricultural datasets. Such approaches can facilitate more precise decisions concerning irrigation, fertilization, crop protection, and production planning. Recent systematic evidence has reported applications of AI and machine learning across crop monitoring, yield prediction, and resource optimization, demonstrating the increasing connection between computational intelligence and agricultural efficiency (Ugwu et al., 2025).

Water management represents one particularly important area in which AI can contribute to agricultural sustainability. Smart irrigation systems can integrate AI with sensors, Internet of Things technologies, weather information, and automated control mechanisms to determine when and how much water should be applied. Recent systematic research on AI-driven smart irrigation has identified water-use efficiency, crop productivity, climate resilience, and sustainability as interconnected outcomes of these technologies. Similar principles can be applied to nutrient and crop-protection management, where AI-based prediction and detection systems may help reduce unnecessary fertilizer and pesticide application while maintaining agricultural productivity. Thus, the contribution of AI should be considered not only in terms of technological accuracy but also in terms of its capacity to improve the efficiency and sustainability of agricultural resource use.

Beyond individual applications, AI is increasingly associated with a broader transformation toward smart and intelligent agriculture. The integration of AI with IoT, remote sensing, robotics, and other digital technologies enables agricultural systems to move from periodic observation toward continuous monitoring and data-driven intervention. Mohammed et al. (2025), for example, identified crop monitoring, irrigation management, weed and pest control, yield prediction, and smart spraying as important areas in which AI contributes to precision agriculture. Their review suggests that AI-supported agricultural systems increasingly combine real-time information with predictive and decision-support capabilities. This development indicates that AI may function not simply as an individual agricultural technology but as an integrating mechanism within increasingly interconnected farming systems.

However, the relationship between AI and sustainability should not be understood as automatically positive. The implementation of AI in agriculture involves technological, economic, organizational, environmental, and ethical challenges. High infrastructure costs, limited digital connectivity, inadequate data quality, lack of technical skills, data ownership, algorithmic bias, and unequal access to digital technologies may restrict the practical benefits of AI, particularly among smallholder farmers. Recent research also emphasizes that the transition from experimental AI models to scalable and equitable agricultural systems remains a major challenge. Therefore, evaluating AI for sustainable agriculture requires consideration of both its technological capabilities and the conditions under which those capabilities can generate meaningful agricultural outcomes.

Although several reviews have examined AI applications in agriculture, the existing literature remains divided across specific technological or agricultural domains. Some reviews focus primarily on crop production and AI algorithms (Ali et al., 2025), while others concentrate on machine learning, precision agriculture, irrigation, soil health, or particular technological combinations. Recent systematic reviews demonstrate the richness of this literature, but they also indicate the need for a broader synthesis that connects AI applications, agricultural resource optimization, and sustainability outcomes within one analytical framework. In particular, it remains important to understand not only which AI technologies are being applied, but also what agricultural resources they address, what sustainability outcomes are reported, and what barriers may influence their effectiveness and scalability.

Therefore, this systematic literature review aims to synthesize research on artificial intelligence for sustainable agriculture, with particular attention to three interconnected dimensions: AI applications, agricultural resource optimization, and sustainability outcomes. The review examines how AI is being applied across agricultural production and management, how these applications contribute to the more efficient use of resources such as water, soil nutrients, fertilizers, pesticides, energy, and labor, and what environmental, economic, and agricultural outcomes are reported. Following systematic-review principles and transparent reporting practices recommended by Page et al. (2021), the study further identifies research gaps, implementation challenges, and emerging directions for AI-enabled sustainable agriculture.

LITERATURE REVIEW

1. Artificial Intelligence in Agricultural Systems

Artificial intelligence has become an important component of digital agriculture because agricultural systems generate increasingly diverse data from sensors, satellites, unmanned aerial vehicles, weather stations, and farm-management platforms. Machine learning and related computational methods can transform these data into predictions and classifications that support agricultural decisions (Widodo et al., 2024; Ajith et al., 2025). In sustainable agriculture, the importance of AI therefore lies not only in automation but also in its capacity to improve the timing, location, and quantity of agricultural interventions. Recent research identifies machine learning as an increasingly important mechanism for integrating agricultural data into predictive and resource-management processes (Mishra et al., 2025).

AI applications are particularly visible in crop monitoring, disease identification, yield prediction, soil assessment, weed detection, and precision management. Computer vision and machine learning, for example, allow agricultural systems to identify crop conditions from visual and remote-sensing information and potentially support interventions before problems become more severe. A recent systematic review of machine learning and computer vision found applications across crop, harvesting, soil, and water management, demonstrating the expanding role of AI within precision agriculture (Kumar et al., 2025).

2. AI for Agricultural Resource Optimization

Resource optimization represents an important link between AI adoption and agricultural sustainability. Precision agriculture technologies enable inputs to be managed according to spatial and temporal variations rather than through uniform application. This approach can reduce unnecessary use of water, fertilizers, pesticides, and other inputs while maintaining agricultural productivity. Getahun et al. (2024) found that precision agriculture technologies can improve the management of crops, soil, and agricultural resources while simultaneously supporting productivity and environmental sustainability (Jabed & Murad, 2024).

Machine learning can further strengthen resource optimization by predicting crop requirements and identifying relationships between environmental conditions and agricultural outcomes. For example, AI-based irrigation systems can combine soil, crop, weather, and sensor information to generate adaptive irrigation schedules. Recent evidence indicates that AI-driven irrigation can contribute to water-use efficiency, energy savings, and crop productivity, particularly when machine learning is integrated with IoT-based sensing and automated control (El-Sayed et al., 2025).

3. AI and Sustainable Crop Production

Sustainable agriculture requires more than increased production; it involves balancing productivity with environmental resource conservation and long-term agricultural resilience. AI can contribute to this balance by supporting more precise crop management, early detection of agricultural problems, and predictive planning. In this context, AI-supported systems may help farmers reduce excessive input application while improving the efficiency of production processes. The sustainability contribution of AI is particularly visible when multiple technologies are integrated. AI combined with remote sensing, IoT, and other precision-agriculture technologies can facilitate continuous monitoring and data-driven intervention. Mgendi (2024) argues that the integration of precision agriculture technologies creates opportunities to improve resource efficiency while reducing environmental impacts associated with agricultural production.

4. Sustainability Outcomes of AI-Based Agriculture

The literature suggests that sustainability outcomes associated with AI can be considered across several dimensions. Environmental outcomes include reduced water consumption, fertilizer losses, pesticide use, and environmental pollution. Economic outcomes may include reduced input costs, improved productivity, and better production planning. Agricultural outcomes include improved crop yields, disease management, and resource-use efficiency. Ugwu et al. (2025), for instance, synthesized evidence showing that AI and machine learning have been applied to crop monitoring, yield prediction, and resource optimization, while also identifying benefits related to water, fertilizer, cost, and production efficiency.

However, sustainability outcomes are not necessarily guaranteed by the introduction of AI. The benefits depend on data quality, infrastructure, technological accessibility, model interpretability, farmer capacity, and the suitability of the technology to specific agricultural contexts. Consequently, AI should be understood as an enabling technology whose sustainability effects depend on how effectively it is integrated into agricultural systems.

5. Research Gap and Positioning of the Present Review

Existing reviews have provided valuable evidence about AI applications, precision agriculture, machine learning, computer vision, and specific resource-management problems. However, much of the literature remains organized around individual technologies or specific applications. For example, some reviews concentrate on machine learning and soil health, others on precision-agriculture technologies, while recent studies focus specifically on AI-driven irrigation or crop management.

The present review therefore positions itself around the relationship between AI applications, resource optimization, and sustainability outcomes. Rather than asking only which AI technologies are used in agriculture, this review examines how those technologies contribute to the more efficient use of agricultural resources and what sustainability outcomes are reported. This positioning provides a basis for synthesizing the literature across different agricultural applications and identifying the conditions, limitations, and future research directions associated with AI-enabled sustainable agriculture.

RESEARCH METHODS

1. Research Design

This study employed a Systematic Literature Review (SLR) to synthesize empirical and scholarly evidence concerning the application of Artificial Intelligence (AI) in sustainable agriculture. The review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) framework to ensure transparency in the identification, screening, eligibility assessment, and inclusion of relevant studies (Page et al., 2021; Saddhono et al., 2024). PRISMA 2020 provides a structured framework for reporting systematic reviews and emphasizes transparent documentation of information sources, search strategies, eligibility criteria, study selection, and synthesis procedures.

The review was designed around three analytical dimensions: (1) AI applications in agriculture, (2) agricultural resource optimization, and (3) sustainability outcomes. This structure enables the study to move beyond a simple inventory of AI technologies and examine how AI contributes to sustainable agricultural practices.

2. Data Source

The primary data source was the Scopus database, selected because of its broad coverage of peer-reviewed international publications across agricultural science, computer science, environmental science, engineering, and sustainability research. Scopus has also been widely used in recent systematic and bibliometric reviews of AI and sustainable agriculture. The review covered publications from January 2020 through December 2025. The 2020–2025 period was selected to capture the recent development of AI-enabled agricultural technologies while maintaining a sufficiently focused publication window. Studies published before 2020 were excluded from the main synthesis even when they were relevant to the broader historical development of AI in agriculture.

The search strategy was constructed around combinations of three core concepts:

(“artificial intelligence” OR “machine learning” OR “deep learning”) AND (“agriculture” OR “smart agriculture” OR “precision agriculture”) AND (“sustainability” OR “sustainable agriculture” OR “resource optimization”)

The search was conducted using title, abstract, and keyword fields. The final search date should be reported in the manuscript as the actual date on which the Scopus search/export was performed.

3. Inclusion and Exclusion Criteria

To ensure consistency in study selection, predefined inclusion and exclusion criteria were applied.

Table 1. Inclusion and Exclusion Criteria

Criterion	Inclusion	Exclusion
Publication period	2020–2025	Before 2020
Language	English	Non-English
Document type	Research articles and review articles	Editorials, notes, conference abstracts, book chapters
Subject	AI applied to agriculture	AI unrelated to agricultural systems
Sustainability relevance	Resource efficiency, environmental, economic, or agricultural sustainability	Studies without a meaningful agricultural or sustainability connection
Accessibility	Publications with sufficient bibliographic/abstract information for screening	Records with insufficient information
Research focus	AI, ML, DL, intelligent systems, or AI-enabled technologies	Conventional agricultural technologies without an AI component

The inclusion criteria were deliberately designed to distinguish AI applications in agricultural systems from studies that merely mention AI as a general technological concept.

4. Data Collection Procedure

The study followed four main stages: identification, screening, eligibility assessment, and inclusion. First, relevant records were retrieved from Scopus using the predefined search string. Bibliographic information, including authors, publication year, title, abstract, keywords, journal, DOI, and citation information, was exported for further analysis. Second, duplicate records were removed. The remaining records were screened based on their titles and abstracts to eliminate studies that did not address AI applications in agriculture or sustainable agricultural practices.

Third, potentially relevant studies were assessed against the predefined eligibility criteria. Particular attention was given to whether the studies demonstrated a substantive relationship between AI and at least one of the study's three analytical dimensions: agricultural application, resource optimization, or sustainability outcome. Finally, studies satisfying all eligibility criteria were included in the qualitative synthesis.

The complete selection process should be presented through a PRISMA 2020 flow diagram, reporting the number of records identified, screened, excluded, assessed for eligibility, and ultimately included.

5. Data Extraction

A structured data-extraction framework was developed to ensure consistency across the selected publications. The extracted information included:

1. Author(s) and publication year
2. Country or geographical context
3. Agricultural sector or crop/application

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4. AI technology or computational approach
5. Agricultural problem addressed
6. Type of agricultural resource optimized
7. Reported agricultural outcomes
8. Environmental sustainability outcomes
9. Economic or productivity outcomes
10. Implementation challenges
11. Future research recommendations

The resource-optimization category included water, fertilizer, pesticides, soil nutrients, energy, land, labor, and other agricultural inputs, depending on the evidence reported in each study.

6. Data Analysis

The selected studies were analyzed using descriptive and thematic synthesis. Descriptive analysis was used to identify publication patterns across the 2020–2025 period, including publication year, agricultural application areas, AI technologies, geographical contexts, and sustainability-related outcomes.

Thematic analysis was then applied to identify recurring patterns across the literature. The findings were organized into three primary themes:

Theme 1: AI Applications

1) crop monitoring
2) disease and pest detection
3) yield prediction
4) soil analysis
5) smart irrigation
6) precision farming
7) agricultural robotics
8) climate prediction

Theme 2: Resource Optimization

1) water efficiency
2) fertilizer optimization
3) pesticide reduction
4) soil management
5) energy efficiency
6) labor optimization
7) input-use efficiency

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Theme 3: Sustainability Outcomes

1) environmental sustainability
2) agricultural productivity
3) economic efficiency
4) resource conservation
5) climate resilience
6) sustainable farm management

The thematic synthesis was used to identify similarities, differences, research concentrations, and gaps across the selected studies. Particular attention was given to the relationship between AI application → resource optimization → sustainability outcome. This approach is appropriate because recent AI-agriculture reviews have similarly identified resource management, crop improvement, soil health, irrigation, and precision farming as major application areas, while also highlighting continuing challenges involving infrastructure, data availability, and contextual adaptation.

RESULTS

1. Overview of AI Applications in Sustainable Agriculture

The reviewed literature indicates that artificial intelligence is being applied across several major areas of agricultural production and management. The most prominent applications involve crop monitoring, yield prediction, disease and pest detection, irrigation management, soil and nutrient management, and precision farming. Recent systematic reviews consistently identify these areas as major applications of AI and machine learning in agriculture. Mohammed et al. (2025), for example, identified crop monitoring, irrigation, weed and pest control, yield prediction, and smart spraying as major application areas, while a separate review of machine learning and computer vision emphasized crop, harvesting, soil, and water management.

Table 2. Major Applications of AI in Sustainable Agriculture

AI application	Main agricultural function	Sustainability relevance
Crop monitoring	Detecting crop conditions and stress	Early intervention and reduced losses
Yield prediction	Forecasting agricultural production	Better planning and resource allocation
Disease and pest detection	Identifying threats at an early stage	Reduced pesticide use
Smart irrigation	Predicting water requirements	Water conservation
Soil and nutrient management	Estimating soil and crop nutrient needs	Improved fertilizer efficiency
Precision spraying	Targeting pesticides or other inputs	Reduced chemical use
Agricultural robotics	Automating field operations	Labor and input efficiency
Remote sensing + AI	Monitoring large agricultural areas	Site-specific management

Table 2 shows that AI applications are concentrated around activities requiring prediction, monitoring, and targeted intervention. This is important because sustainable agriculture depends increasingly on the ability to identify differences between crops, fields, soil conditions, and environmental conditions rather than applying uniform treatments. AI therefore functions primarily as a **decision-support technology**, helping agricultural actors determine when, where, and how much intervention is required.

2. AI and Agricultural Resource Optimization

A second major finding concerns the relationship between AI and resource optimization. The literature demonstrates that AI is increasingly used to improve the efficiency of water, fertilizers, pesticides, energy, and labor. Rather than replacing agricultural resources, AI helps determine how those resources can be allocated more precisely.

Table 3. Resource Optimization through AI

Resource	AI-supported application	Expected sustainability benefit
Water	Smart irrigation and water-demand prediction	Reduced water consumption
Fertilizer	Nutrient prediction and variable-rate application	Improved nutrient-use efficiency
Pesticides	Pest/disease prediction and precision spraying	Reduced chemical application
Energy	Intelligent irrigation and automated machinery	Lower energy requirements
Labor	Robotics and automated monitoring	Reduced labor requirements
Land/input use	Precision management	More efficient agricultural production

The strongest evidence concerns water and input optimization. AI-based irrigation systems can combine machine learning, sensors, and IoT technologies to monitor soil–plant conditions and adjust irrigation schedules. Recent evidence shows that these systems can improve water-use efficiency while also supporting crop productivity and energy savings. Similarly, AI-supported crop management has been associated with reductions in fertilizer and pesticide use because agricultural inputs can be applied according to predicted crop requirements or detected threats rather than uniformly across a field. Ugwu et al. (2025), for example, synthesized evidence reporting improvements in water and fertilizer efficiency alongside productivity gains.

3. Sustainability Outcomes

The third major finding is that AI applications are associated with sustainability outcomes across environmental, agricultural, and economic dimensions.

Table 4. Reported Sustainability Outcomes

Sustainability dimension	Main outcomes identified
Environmental	Reduced water use, fertilizer use, pesticide application, and nutrient losses
Agricultural	Improved crop monitoring, yield prediction, disease management, and productivity
Economic	Lower input costs, improved efficiency, and better production planning
Climate resilience	Improved prediction, adaptive irrigation, and better response to environmental variability
Resource sustainability	More efficient use of water, nutrients, energy, and other inputs

The findings indicate that AI contributes to sustainability through a chain of effects rather than through a single outcome. Better prediction and monitoring can lead to more precise agricultural decisions; these decisions can reduce unnecessary resource consumption; and improved resource efficiency can subsequently contribute to environmental and economic sustainability.

For example, the systematic review by Ugwu et al. (2025) reported improvements in yield, water savings, fertilizer efficiency, cost reduction, and operational efficiency across the reviewed literature. Similarly, research on AI-driven irrigation identifies improved water-use efficiency, energy savings, and crop productivity as interconnected outcomes.

4. Emerging Integration of AI with Other Technologies

Another pattern identified in the literature is that AI increasingly operates as part of an integrated agricultural technology ecosystem rather than as a stand-alone technology. AI is frequently combined with IoT sensors, remote sensing, computer vision, UAVs, robotics, and automated control systems.

Table 5. AI and Complementary Agricultural Technologies

Technology	Contribution when combined with AI
IoT sensors	Real-time agricultural data
Remote sensing	Large-scale crop and environmental monitoring
UAVs/drones	High-resolution field observation
Computer vision	Automated crop/disease recognition
Robotics	Automated agricultural intervention
Cloud/data platforms	Data storage and processing
Automated control systems	Real-time implementation of AI decisions

The integration of these technologies creates a transition from simple data collection toward intelligent agricultural decision-making. For example, sensors collect information, AI analyzes the information, and automated systems can subsequently implement the recommended intervention. Recent systematic reviews identify this convergence of AI, IoT, computer vision, and robotics as an important direction in precision agriculture.

5. Major Challenges

Despite the reported benefits, the literature also identifies several barriers to the effective implementation of AI in sustainable agriculture.

Table 6. Major Challenges Identified

Challenge	Implication
Poor data quality	Reduces prediction reliability
High implementation cost	Limits accessibility
Limited digital infrastructure	Restricts deployment in rural areas
Lack of technical skills	Limits effective technology use
Model interpretability	Makes some AI outputs difficult to trust
Data ownership and privacy	Creates governance concerns
Digital inequality	May disadvantage smallholder farmers
Limited interoperability	Makes technology integration difficult

The findings suggest that AI does not automatically produce sustainable outcomes. Its effectiveness depends on the availability of reliable data, infrastructure, technical capacity, and appropriate institutional support. Ugwu et al. (2025) specifically identified poor data quality, expensive infrastructure, limited digital literacy, data ownership, and algorithmic bias as continuing barriers.

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The issue of interpretability is also important. Although deep-learning approaches may provide strong predictive performance, their complexity can make it difficult for agricultural users to understand why a particular recommendation has been generated. This creates a potential gap between technical accuracy and practical usability.

6. Overall Synthesis of the Findings

Taken together, the results indicate that AI contributes to sustainable agriculture primarily through the following pathway:

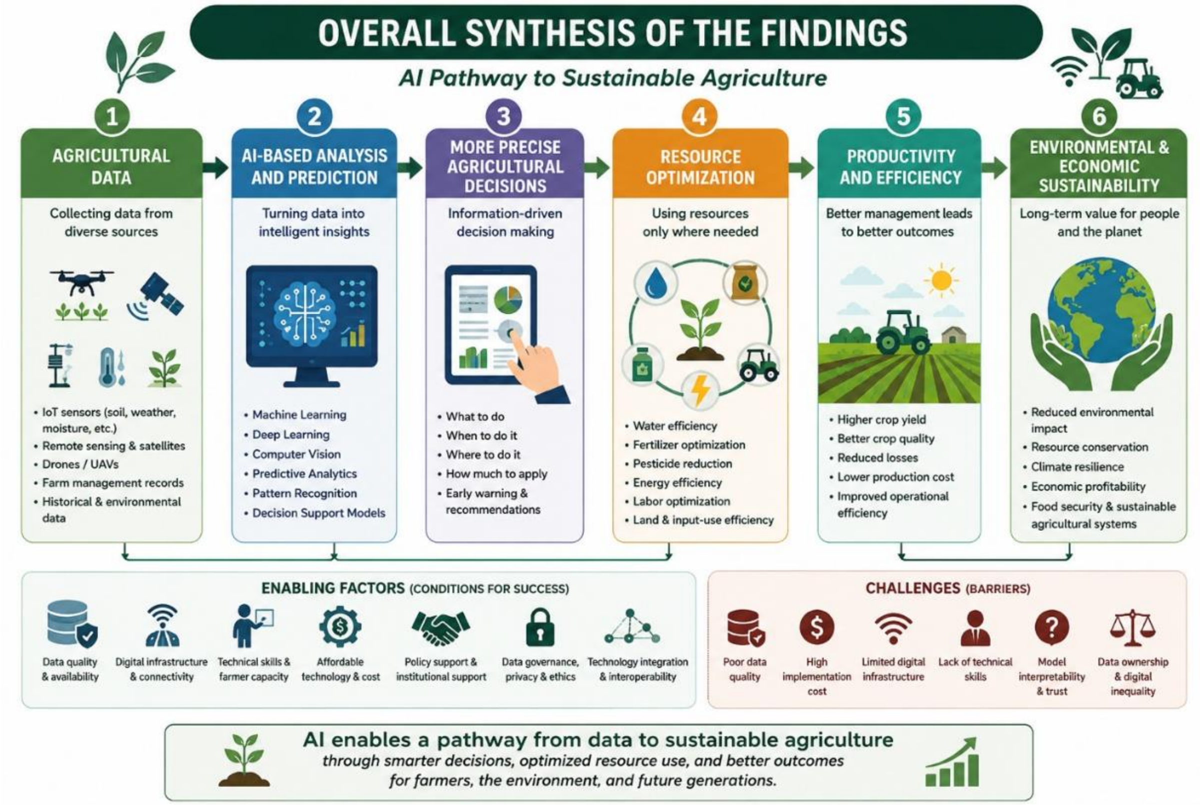

Figure 1. Finding of AI Pathway to Sustainable Agriculture

The central finding is therefore not simply that AI is increasingly used in agriculture. Rather, the literature suggests that the sustainability value of AI emerges when technological capabilities are translated into more precise resource-management decisions. This interpretation is consistent with earlier systematic evidence showing that AI is increasingly being applied to prediction, crop management, resource management, weed control, and other agricultural functions, while more recent reviews demonstrate growing integration with IoT, computer vision, and precision-agriculture systems.

DISCUSSION

1. AI Applications as a Pathway toward Sustainable Agriculture

The findings indicate that artificial intelligence is increasingly positioned as a decision-support mechanism within agricultural systems rather than simply as a stand-alone technology. AI applications in crop monitoring, disease detection, yield prediction, irrigation, soil management, and precision farming demonstrate that the main contribution of AI lies in converting agricultural data into actionable information. This finding is consistent with the broader development of digital agriculture, in which data-driven technologies are increasingly used to improve the precision and timeliness of farm management decisions.

The concentration of AI applications around monitoring, prediction, and early detection is particularly important for sustainability. When crop conditions, water requirements, diseases, or production outcomes can be predicted earlier, agricultural interventions can potentially be performed before problems become more severe. Thus, the value of AI is not only its computational capability but also its ability to support more proactive agricultural management.

2. Resource Optimization as the Main Link between AI and Sustainability

A central finding of the review is that resource optimization provides an important pathway through which AI contributes to sustainable agriculture. Water, fertilizers, pesticides, energy, and labor are increasingly managed through data-driven approaches. Rather than applying agricultural inputs uniformly, AI-supported systems enable decisions to respond to variations in crop condition, soil characteristics, weather, and field location.

This finding suggests that AI contributes to sustainability most directly when it improves input-use efficiency. For example, intelligent irrigation can determine when irrigation is required, while disease-detection systems can help identify areas requiring treatment. Consequently, sustainability is achieved not simply because AI is introduced into agriculture, but because AI can help reduce unnecessary interventions while maintaining agricultural productivity.

3. Integration with Other Technologies

Another important finding is the increasing integration of AI with IoT sensors, remote sensing, UAVs, computer vision, robotics, and automated systems. This integration suggests that the future of AI in agriculture will increasingly involve interconnected technological ecosystems rather than isolated applications. For example, sensors and remote-sensing technologies can provide agricultural data, AI can process and interpret those data, and automated systems can subsequently implement recommendations. Such integration creates the possibility of a more responsive agricultural system in which monitoring, prediction, decision-making, and intervention are connected.

However, this development also increases the importance of technological compatibility, infrastructure, and data management. The effectiveness of AI therefore depends partly on the broader digital ecosystem in which it operates.

4. Challenges and Practical Implications

Although the literature reports substantial potential benefits, the findings also show that AI implementation faces several barriers. Data quality, implementation costs, digital infrastructure, technical skills, model interpretability, and digital inequality can limit the practical adoption of AI. These challenges are particularly relevant to agricultural contexts where farmers may have different levels of access to technology and technical expertise. This means that technological development alone is insufficient to guarantee sustainable agricultural transformation. AI solutions need to be affordable, understandable, accessible, and adapted to local agricultural conditions. Greater attention should therefore be given to farmer capacity building, infrastructure development, data governance, and technology interoperability.

5. Overall Interpretation

Overall, the findings demonstrate that AI has considerable potential to support sustainable agriculture, but its contribution is best understood as a pathway rather than an automatic outcome. AI provides analytical and predictive capabilities; these capabilities can support better agricultural decisions; better decisions can improve resource efficiency; and improved resource efficiency can contribute to environmental, economic, and agricultural sustainability. The central interpretation of this review can therefore be summarized as AI does not create sustainable agriculture by itself. Rather, AI enables more sustainable agriculture when its analytical capabilities are translated into precise decisions, efficient resource use, and measurable agricultural outcomes.

This perspective provides a useful basis for future research to move beyond questions of whether AI works toward questions of where, how, and under what conditions AI can produce meaningful sustainability benefits in agricultural systems.

CONCLUSION

This systematic literature review examined the role of Artificial Intelligence (AI) in sustainable agriculture, with particular attention to AI applications, agricultural resource optimization, and sustainability outcomes. The findings indicate that AI is increasingly applied to crop monitoring, yield prediction, disease and pest detection, irrigation management, soil and nutrient management, precision farming, and agricultural automation. A major finding is that resource optimization represents an important pathway connecting AI with agricultural sustainability. AI-supported systems can help improve the use of water, fertilizers, pesticides, energy, labor, and other agricultural inputs by enabling more precise and data-driven decisions. These improvements have the potential to contribute to higher agricultural efficiency while reducing unnecessary resource consumption.

The review also demonstrates that AI is increasingly integrated with IoT sensors, remote sensing, UAVs, computer vision, robotics, and automated systems. Such integration supports a transition from conventional agricultural management toward more intelligent and responsive farming systems. Nevertheless, the sustainability benefits of these technologies depend on appropriate infrastructure, reliable data, technical capacity, affordability, and effective technology integration. Overall, the review concludes that AI does not automatically produce sustainable agriculture. Rather, its contribution depends on how effectively AI-generated information is translated into agricultural decisions and practical interventions. Future research should move beyond evaluating AI primarily through technical performance and give greater attention to real-world agricultural impacts, long-term sustainability, accessibility for smallholder farmers, cost-effectiveness, data governance, and responsible AI implementation. Such a direction is essential for ensuring that advances in AI contribute not only to smarter agriculture but also to more environmentally, economically, and socially sustainable agricultural systems.

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