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AI-Driven Transformation in Sustainable Agriculture: A Systematic Review

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ABSTRACT

The agriculture sector is facing unprecedented pressure from a rapidly growing global population, erratic weather conditions and declining water availability. Traditional farming methods are increasingly proving insufficient in meeting the rising food demand, necessitating a shift towards technology-driven solutions. This paper provides a critical and systematic review of the application of Artificial Intelligence (AI) in agriculture, analysing its impact on productivity and sustainability, while identifying potential barriers hindering adoption. Employing a Systematic Literature Review approach, this study synthesizes recent research organized around the core domains of agricultural production-crop, soil and nutrient, water and irrigation and crop-protection (pest, disease and weed) management, alongside yield forecasting-examining how data-driven tools such as machine learning, the internet of things, robotics and computer vision are applied within each and prioritizing studies that reported agronomically meaningful outcomes such as yield gains and resource-use efficiency. The strongest gains identified across the review fall within three agricultural areas-crop and soil monitoring, yield forecasting and robotic field operations such as targeted detection, weeding and harvesting. The technologies enabling them, chiefly machine-learning models such as convolutional neural networks combined with field and remote sensors, have delivered high in-field precision, with reported object-detection precision of up to 95.78% in field conditions. In practical terms, this translates into more efficient use of water, fertilizer and other inputs and into improved yield and crop quality. The review concludes that prioritizing explainable AI and interoperable farm systems is central to building farmer trust and safeguarding food security under a changing climate.

Key words: Artificial intelligence, Crop management, Machine learning, Precision agriculture, Smart farming, Sustainable agriculture.

The global agricultural landscape is at a critical juncture. The rising global population is exerting increasing pressure on food supply. This is further exacerbated by challenges such as water scarcity and climate instability. Artificial Intelligence has e merged as a transformative force, moving farm processes beyond simple automation and influencing both the quantity and quality of agricultural output (Elbasi *et al.*, 2022). This technological integration is pivotal for advancing sustainable agriculture and ensuring food security amidst complex environmental and demographic pressures (Zhang *et al.*, 2025). In this context, smart agriculture can be understood as a management approach that seeks to sustain or raise productivity and food security in the face of variable growing conditions and a changing climate, while responding to growing expectations of transparency from all actors along the agri-food chain (Sharma and Shivandu, 2024).

AI enables “Smart Farming” by integrating technologies such as expert systems, natural language processing and machine vision, demonstrating how intelligent systems can be applied to boost productivity (Oliveira and Silva, 2023). This paradigm shift is characterized by the integration of AI with IoT to form an AIoT ecosystem, facilitating real-time data analysis, predictive modelling and automated decision-making across various agricultural domains (Khaled *et al.*, 2025). AIoT systems optimize resource utilization and enhance crop yields, thereby facilitating precision agriculture through applications such as soil management, crop health monitoring, disease detection and weed control (Hussein *et al.*, 2024a; Sharma and Shivandu, 2024). Precision agriculture has been further enhanced by adaptive AI technologies, including machine learning, computer vision and sensor technologies, allowing for real-time monitoring and control of farm conditions (Akintuyi, 2024a; Hussein *et al.*, 2024b). Technological integration at this level enables farmers to make data-driven decisions, optimizing inputs like water and fertilizers, consequently reducing environmental impact and promoting long-term sustainability (Sonawane, 2024). The adoption of AI-driven solutions is furthermore crucial for mitigating the adverse effects of climate change on agricultural productivity and for ensuring the resilience of food systems (Debnath *et al.*, 2024). The integration of AI into agricultural practices is therefore imperative for

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meeting the projected 70% increase in food production by 2050 to feed the growing world population, especially given the challenges posed by climate change (Garcia-Aguero *et al.*, 2023; Zidan and Febriyanti, 2024).

The importance of this transition can further be attributed to improving farmers' profitability and the broader national economy (Elbasi *et al.*, 2022). However, despite its potential, the adoption of AI is restricted by research gaps related to model reliability and the socioeconomic barriers faced by farmers particularly in developing regions (Aijaz *et al.*, 2025). This review paper aims to bridge these gaps by providing a comprehensive systematic review of current AI technologies, their applications, impacts and prospective areas of deployment within the agricultural sector.

This study follows a systematic literature review methodology to examine how artificial intelligence is being applied to address production challenges across the agricultural sector. Rather than treating the underlying technologies as the object of study, the review is organized around the principal domains of agricultural production-crop and cropping-system management, soil and nutrient management, water and irrigation management, crop protection (pest, disease and weed management), yield forecasting and allied livestock and post-harvest systems and examines how data-driven tools such as machine learning, the Internet of Things, robotics and computer vision are deployed within each (Oliveira and Silva, 2023). Peer-reviewed journal articles and conference proceedings were screened for their relevance to these farming systems and to the broader goals of precision agriculture, smart farming and agricultural sustainability. Priority was given to studies reporting agronomically meaningful outcomes-gains in crop yield, water and input-use efficiency, early detection of pests and diseases and farm-level resource savings-rather than algorithmic performance alone (Aijaz *et al.*, 2025; Elbasi *et al.*, 2022). Articles published between 2010 and 2025 were included to capture contemporary advances in the field (Akintuyi, 2024b), while studies lacking substantive methodological detail, or with no direct bearing on agricultural production, were excluded. The review followed the systematic literature review guidelines of Kitchenham and Charters (2007), which are widely applied in computing and AI research, structuring the work around predefined research questions, explicit inclusion and exclusion criteria and a consistent data-extraction and synthesis procedure to minimize bias and strengthen the reliability and validity of the findings, an approach consistent with recent systematic reviews of machine learning in agriculture (Araujo *et al.*, 2023).

This problem-led approach enabled a structured assessment of how AI integration translates into measurable gains within agricultural systems, with key findings, methods and quantitative outcomes extracted and grouped by production domain (Seif-Ennasr *et al.*, 2025; Vasileiou *et al.*, 2023). To keep the synthesis centered on agriculture, the review was guided by three research questions framed around the needs of the sector: (i) which agricultural production challenges and farming-system domains are being addressed through AI-based approaches and what tools are applied within each; (ii) what documented gains in crop productivity, yield and resource-use efficiency have resulted from these applications and (iii) what technical, socioeconomic and ethical barriers continue to constrain their large-scale, on-farm adoption. These questions provided a consistent framework for data extraction, thematic categorization by agricultural domain and comparative analysis across the selected studies.

AI applications in agriculture sectors

Artificial intelligence has penetrated all walks of life and agriculture has not remained an exception to it. With the use of innovative technologies and methods and sophisticated instruments, AI has greatly improved the accuracy and productivity of agricultural operations, entirely changing the crop monitoring and management framework (Subeesh and Mehta, 2021). While crop management focuses on the efficient utilization of land resources (Atzberger, 2013; Kreuze *et al.*, 2022), water management primarily aims to optimize irrigation practices, minimizing wastage and enhancing water use efficiency (Khanna and Kaur, 2019; Koech and Langat, 2018). Soil management is also crucial, as it directly influences the effectiveness of site-specific crop management, ensuring the balanced application of inputs for environmental sustainability and economic efficiency (Carter and Johannsen, 2017). A schematic overview of the principal AI technologies and the major agricultural sectors in which they are applied is presented in Fig 1.

Irrigation systems have been extensively integrated with nutrient delivery systems to develop fertigation systems as an effective strategy to enhance fertilizer use efficiency (Karasahin *et al.*, 2018). IoT-based fertigation platforms combine soil and canopy sensing with automated dosing so that nutrient supply tracks actual crop demand rather than a fixed calendar, which is where their gains in fertilizer-use efficiency arise (Lin *et al.*, 2020). In addition, crop prediction-particularly yield forecasting-has gained significant importance for improving resource planning, risk management and sustainability in agricultural systems (Vashisht *et al.*, 2022). Here, a systematic synthesis of the field found artificial neural networks to be the most frequently applied model class, with temperature, rainfall and soil type the most commonly used predictors (Van Klompenburg *et al.*, 2020). Hybrid deep-learning architectures, such as CNN-LSTM models with attention mechanisms, have further improved yield-prediction accuracy for wheat and rice under Indian conditions (Kalmani *et al.*, 2025). Image processing and deep learning techniques have enabled more precise and automated identification of crop types, considerably

advancing the crop classification process (Chen *et al.*, 2022).

Modern agriculture also relies strongly on early detection and effective management of plant diseases and pests, owing to their detrimental impacts on productivity and crop quality (Cho, 2024; Lucas, 2011). Across these domains, the reviewed studies report quantitative benchmarks that indicate the scale of the gains achieved. In robotic field operations, a machine-vision kiwifruit harvester picked 51.0% of the fruit in commercial orchards at an average cycle time of 5.5 s per fruit (Williams *et al.*, 2019), while a Mask-RCNN detector localized ripe strawberries with 95.78% precision and 95.41% recall, permitting picking-point estimation with an average error of ±1.2 mm (Yu *et al.*, 2019). In crop protection, an ensemble of convolutional neural networks classified three major citrus pests with 99.04% accuracy under field imaging conditions (Khanramaki *et al.*, 2021) and VGG16-based transfer learning attained leaf-disease classification accuracies of 98.40% for grape and 95.71% for tomato (Paymode and Malode, 2022). Classification of date fruit varieties with a MobileNetV2 architecture likewise reached 99% accuracy (Albarrak *et al.*, 2022). Comparable gains are documented on the resource side: Machine-learning estimation of reference evapotranspiration refines irrigation scheduling and water-use efficiency (Reis *et al.*, 2019), low-cost IoT irrigation modules curtail water wastage in smallholder settings (Nawandar and Satpute, 2019), AI-driven precision irrigation has likewise demonstrated measurable gains in water-use efficiency under Indian field conditions (Kim and AlZubi, 2024) and smart fertigation management improves fertilizer-use efficiency while reducing nutrient losses to the environment (Karasahin *et al.*, 2018; Lin *et al.*, 2020). These figures anchor the qualitative claims of the problem-led synthesis in measurable improvements in input use, operational efficiency and output quality across the domains examined. A wide range of AI-based approaches has thus been implemented across various agricultural domains (Table 1), many of which have empirically demonstrated strong performance in quality assessment, predictive analytics and decision-making accuracy; the principal quantitative benchmarks reported in these studies are consolidated in Table 2.

AI-driven genetic modification and resource utilization

AI plays an increasingly important role in crop breeding and genetic modification, supporting the development of disease and pest-resistant crops and of varieties tolerant to environmental stress (Hafeez *et al.*, 2023; Rai, 2022). This has helped optimize the use of critical resources such as water, fertilizers and pesticides, enhancing agricultural efficiency. Analysis of large-scale genetic datasets and their interaction with environmental factors enables the AI systems to predict favourable genetic modifications that improve crop productivity (Nolan, 2023).

AI-assisted identification of genes associated with drought tolerance also facilitates the cultivation of crops in regions previously regarded as unsuitable, improving overall agricultural output (Khan *et al.*, 2022).

In addition, AI-driven genetic analysis can also identify other desirable traits, such as improved nutritional quality, accelerated growth rates and reduced dependence on chemical inputs such as fertilizers and pesticides. Additionally, AI-based systems promote fertilizer efficiency by enabling precise application of agrochemicals. This is achieved by minimizing the overuse of fertilizers and reducing their environmental impacts such as soil degradation and water contamination. Overall, the core idea of balancing productivity enhancement and environmental sustainability to ensure long-term global food security, is achieved by application of AI (Kumar and Agrawal, 2020).

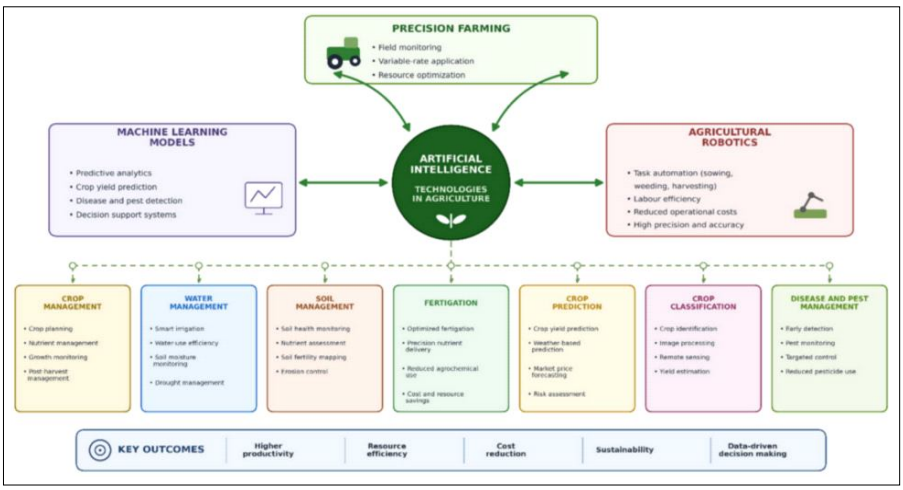


Fig 1: AI used in various agriculture sectors.

AI technologies used in agriculture

AI in agriculture is driven by a convergence of advanced computational techniques and hardware systems. These techniques are becoming faster, more accurate and more deeply integrated into farm systems each year.

Machine learning and deep learning

ML algorithms enable AI systems to learn about physiography and plant characteristics through supervised and unsupervised learning, thus making them critical for precision agriculture (Adewusi *et al.*, 2024). Deep learning, particularly convolutional neural networks, is widely used for image-based tasks (Oliveira and Silva, 2023). These neural networks excel in tasks such as disease detection, crop yield prediction and automated weed recognition due to their capacity for processing complex visual data (Adewusi *et al.*, 2024). Once trained on agricultural data, such systems can perform a multitude of actions including but not limited to monitoring and predicting climatic variables like temperature and humidity, soil moisture, crop

Table 1: Major application domains of AI technologies in modern agriculture.

Application domain	Description	Key outcomes	References
Crop management	Encompasses the planning and execution of farm operations, including sowing, crop maintenance, harvesting, storage and distribution to improve productivity and operational efficiency.	Robotic kiwifruit harvester picked 51.0% of orchard fruit at 5.5s/fruit under commercial conditions; cloud-based UAV analytics streamline orchard inventory and management decisions	(Ampatzidis *et al.*, 2020; Pylianidis *et al.*, 2021; Talaviya *et al.,* 2020; Tivy, 2014; Williams *et al.,* 2019; Wolfert *et al.,* 2017)
Water management	Involves the efficient utilization of water resources through intelligent irrigation systems, monitoring techniques and optimization strategies to enhance water-use efficiency.	Machine-learning estimation of reference evapotranspiration refines irrigation scheduling, low-cost IoT irrigation modules curtail water wastage and improve water-use efficiency.	(Madsen, 1995; Nawandar and Satpute, 2019; Reis *et al.,* 2019; Talaviya *et al.,* 2020; Veerachamy *et al.,* 2022)
Soil management	Focuses on maintaining soil health by assessing nutrient availability, structure and fertility to support sustainable crop growth and long-term productivity.	IoT-deep learning frameworks enable continuous soil-condition monitoring and early anomaly detection, supporting balanced input application	(Delnevo *et al.,* 2022; Madsen, 1995; Singh *et al.,* 2021)
Fertigation	Refers to the application of fertilizers through irrigation systems, enabling precise nutrient delivery, improved absorption and efficient resource use.	Sensor-driven fertigation delivers nutrients in precise doses, improving fertilizer-use efficiency and reducing nutrient losses to the environment.	(Cambra Baseca *et al.*, 2019; Lin *et al.,* 2020)
Crop prediction	Deals with estimating crop yield and production trends using predictive models, supporting strategic planning and decision -making in agriculture.	Machine-learning yield-prediction models improve forecast reliability, supporting resource planning and risk management.	(Bali and Singla, 2022; Van Klompenburg *et al.,* 2020)
Crop classification	Involves identifying and categorizing crops using data-driven and image-based techniques, aiding in agricultural mapping and resource planning.	Deep-learning classifiers reached 99% accuracy for date fruit varieties and 95.78% detection precision for ripe strawberries.	(Albarrak *et al.,* 2022; Selea and Pslaru, 2020; Yu *et al.,* 2019)
Disease and pest management	Focuses on the detection, monitoring and control of plant diseases and pests to minimize crop losses and maintain yield quality through timely interventions.	Ensemble CNNs classified citrus pests with 99.04% accuracy; VGG16 transfer learning achieved 98.40% (grape) and 95.71% (tomato) leaf-disease classification accuracy.	(Delnevo *et al.,* 2022; Khanramaki *et al.,* 2021; Lucas, 2011; Paymode and Malode, 2022; Yuan *et al.,* 2022)

yield and plant diseases (Singh and Sobti, 2021). Such advancements in ML and DL facilitate enhanced decision-making for farmers by providing real-time and accurate insights into crop health and environmental conditions, thereby optimizing agricultural practices (Kamilaris and Prenafeta-Boldú, 2018). For instance, various ML models, including Support Vector Machines, Convolutional Neural Networks and random forests, have been successfully applied to optimize irrigation, fertilization and pest management strategies (Miller *et al.*, 2025).

Computer vision and image processing

This integration enables detailed analysis of plant morphologies, phenotypes, growth anomalies and pathogen presence through advanced imaging techniques (Kashyap *et al.*, 2024). Computer vision, in conjunction with deep learning, facilitates the extraction of meaningful information from visual data such as images. This is essential for the execution of tasks such as automated phenotyping, disease early warning and robotic harvesting (Mustaza *et al.*, 2025; Patrício and Rieder, 2018). Furthermore, these technologies are pivotal in automating quality assessment of agricultural products and precise application of agrochemicals, leading to enhanced efficiency and reduced wastage (Subedi, 2023).

Internet of things and sensor systems

Huge quantities of data regarding various soil characteristics like temperature, humidity and soil moisture are collected using sensors for soil sampling (Elbasi *et al.*, 2022). These devices enable prompt data dissemination to cloud-based services for further analysis (Oliveira and Silva, 2023). This synergy between IoT and AI creates a unique AIoT framework enabling real-time monitoring of crop health parameters and environmental conditions, facilitating predictive analytics for optimized resource allocation and early anomaly detection (Alazzai *et al.*, 2024a; Padhiary, 2024). Moreover, the integration of IoT with deep learning models, such as convolutional neural networks, allows for sophisticated analysis of images captured by drones or ground-based sensors, enabling applications like disease detection, yield estimation and soil condition assessment (Ameer *et al.*, 2024).

Robotics and automation

The reliance on manual labour is significantly reduced by the deployment of agricultural robotics for tasks such as autonomous harvesting, precise application of fertilizer, *etc.* (Elbasi *et al.*, 2022; Oliveira and Silva, 2023). The operational precision and efficiency of sustainable farming practices is further enhanced by the robotic systems, which are often integrated with AI algorithms and computer vision. Agricultural robotics when coupled with computer vision is widely applied in diagnosing pests and soil defects. This has been particularly illustrated by systems like Plantix and Trace Genomics, which leverage deep learning to identify potential issues and optimize soil health (Alreshidi, 2019). Another significant advancement is seen in the domain of crop surveillance and management, where AI-driven drones, equipped with high-resolution cameras and multispectral sensors, are used to capture detailed imagery for comprehensive analysis (Akintuyi, 2024c; Ongadi, 2024),

Table 2: Performance of AI applications across agricultural operations.

AI operation	Technique/model	Crop/system	Reported performance	Reference
Fruit detection for robotic harvesting	Mask-RCNN	Strawberry	95.78% precision, 95.41% recall; picking-point error± 1.2 mm	Yu *et al.* (2019)
Autonomous harvesting	Machine vision with multi-arm robot	Kiwifruit	51.0% of orchard fruit harvested at 5.5 s per fruit	Williams *et al.* (2019)
Pest classification	Ensemble of CNNs	Citrus	99.04% accuracy (10-fold cross-validation, field images)	Khanramaki *et al.* (2021)
Leaf-disease classification	VGG16 transfer learning	Grape; tomato	98.40% (grape) and 95.71% (tomato) classification accuracy	Paymode and Malode (2022)
Variety classification	MobileNetV2	Date fruit	99% classification accuracy	Albarrak *et al.* (2022)
Yield forecasting	Artificial neural networks (most applied class)	Multiple crops	Temperature, rainfall and soil type identified as leading predictors	Van Klompenburg *et al.* (2020)
Irrigation scheduling	ML estimation of reference evapotranspiration	Multiple systems	Improved irrigation scheduling and water-use efficiency	Reis *et al.* (2019)
Smart irrigation	Low-cost IoT module	Smallholder plots	Reduced water wastage in irrigation	Nawandar and Satpute (2019)
Fertigation	IoT sensing with automated dosing	Multiple systems	Improved fertilizer-use efficiency and reduced nutrient losses	Lin *et al.* (2020)

although cost, regulatory and skill-related barriers continue to constrain large-scale drone deployment in Indian agriculture (Sangode, 2025).

Big data and cloud computing

The digitization of farming allows for the handling and management of large data volumes, thereby supporting complex system optimization and planning (Oliveira and Silva, 2023). The AI enabled systems contribute by analysing the huge volume of agricultural big data, acting as an expert system distilling valuable information and ultimately enhancing agricultural productivity (Yang *et al.*, 2020). Cloud computing further enhances the capabilities of these systems by providing scalable and decentralised infrastructure for storing and processing the vast datasets generated by IoT devices and AI models (Alazzai *et al.*, 2024b). This synergy allows multiple stakeholders to work on the same platform simultaneously, enables advanced analytics and facilitates the deployment of sophisticated AI models for predictive analysis and course correction across diverse agricultural domains. Collectively, such technological integrations are critical to transforming traditional agricultural practices into data-driven, precision-oriented systems that enhance efficiency contributing to sustainability (Issa *et al.*, 2024; Mandapuram *et al.*, 2019).

Challenges and limitations

Despite presenting significant opportunities to the farming sector, the AI-integrated agriculture systems encounter many roadblocks. Maintenance of a huge technological infrastructure is a capital intensive exercise and in fact is the biggest hurdle to adoption of AI in agriculture, especially by small and marginal farmers from developing countries. Small landholdings and irregular field terrain further restrict the deployment of precision-agriculture implements in Indian conditions (Mohan Sai *et al.*, 2023). Invariably, this also includes challenges related to constant upgradation and modification of AI frameworks (Qazi *et al.*, 2022; Sharma *et al.*, 2022). A further difficulty is that many models report only what happened in the field or to the animals, without sufficient reasoning as to how they reached that conclusion. This lack of interpretability creates a trust deficit in farmers, hindering adoption (Tedeschi, 2019, 2023). Addressing this deficit requires that explainability be built into the decision pipeline rather than appended to it. In a farming context, Explainable AI can take several practical forms: feature-attribution methods that indicate which agronomic variables-soil moisture, canopy temperature, or leaf spectral signatures-drove a recommendation to irrigate or spray; visual saliency maps that overlay a disease diagnosis on the affected leaf regions so that the farmer can verify the symptom against the model's evidence and calibrated confidence scores that distinguish recommendations the model is certain of from those requiring confirmation by an agronomist or extension worker. Delivered through advisory interfaces in local languages, such explanations convert an opaque prediction into a claim the farmer can check against field experience, providing the reasoning basis on which trust in automated decisions regarding crop health and irrigation can realistically be built (Tedeschi, 2023). Data variability also poses a different set of challenges. Variation is seen not only in agricultural practices but also in crops, soil types, topography and weather and it occurs across regions and even from farm to farm. Since existing AI models are trained on datasets taken from a few specific locations, they may fail to function effectively elsewhere, as they cannot fully account for these variations in time and space (Shrestha, 2024).

Digital divide is another area of concern highlighting limitations at the human resource level. Farmers, particularly in remote and lower-income regions often lack access to the infrastructure required for wireless broadband connectivity, consequently limiting their access to large datasets and cloud-based AI applications. Lack of technical proficiency on part of farmers and agricultural workers, needed for effective utilization of AI tools, is a major concern regarding adoption of AI in agriculture and training of manpower is therefore a crucial requirement for its implementation (Morota *et al.*, 2018). In addition, hyper-connected cyber-networks pose a serious threat to the security of cyberspace, particularly the IoT data and the aggregation of geospatial data. Data obtained from satellite images across multiple farms for large-scale analysis adds an additional layer of risk. In addition to these concerns, the data used in agricultural AI applications typically carries digital footprints of specific locations, communities and environmental conditions. This data, if not handled responsibly, can be used to adversely reinforce the differences between large and small farms, or wealthy and poor farms (Klerkx and Rose, 2020).

CONCLUSION

The evidence synthesized shows that crop monitoring and farm management practices have been substantially transformed by the convergence of AI and IoT within precision agriculture systems. The findings of this study underscore that AI-driven approaches, like machine learning, robotics and precision farming techniques, have strong potential to improve yield outcomes, enhance operational efficiency and reduce environmental impacts. AI driven advanced technologies such as image processing, computer vision and spectral imaging have enabled more accurate crop identification, yield prediction and disease monitoring.

This study has identified seven major domains in agriculture for AI application: crop management, water management, soil management, fertigation, crop prediction, crop classification and disease and pest management. Despite the advancements, the large-scale adoption of AI technologies is restricted by limited digitization and data integration in small and medium-sized farming systems. Going forward, AI holds unparalleled potential to

improve agricultural sustainability through optimized resource utilization and data-driven decision-making. Enhanced precision in resource management and increment in crop productivity are expected with continued advancements in AI. However, broader adoption of AI in agriculture will still require increased investment in infrastructure, increased access to technological resources and training of manpower.

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Disclaimers

The views and conclusions expressed in this article are solely those of the authors and do not necessarily represent the views of their affiliated institutions. The authors are responsible for the accuracy and completeness of the information provided, but do not accept any liability for any direct or indirect losses resulting from the use of this content.

Informed consent

This review article is based entirely on previously published literature and did not involve any new studies with human participants or animals performed by the authors informed consent and ethical approval are therefore not applicable.

Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this article. No funding or sponsorship influenced the design of the study, data collection, analysis, decision to publish, or preparation of the manuscript.

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