International Journal of Farm Sciences **16(2-3):** 72-85, 2026; **doi: 10.5958/2250-0499.2026.00026.9**

Review

Harnessing artificial intelligence for sustainable and data-driven agriculture

DEEPAK SHARMA*

School of Agricultural Sciences, Baddi University of Emerging Sciences and Technology Baddi, Solan 173205 Himachal Pradesh, India

*Email for correspondence: deepak.kakusharma@gmail.com

Received: 02.04.2026/Accepted: 18.05.2026

ABSTRACT

Agriculture is undergoing a major transformation driven by artificial intelligence (AI), shifting traditional farming toward a more data-driven and technology-enabled system. This review explores the role of AI in modern agriculture, focusing on its key components, applications, benefits, limitations and future prospects. AI technologies such as machine learning, deep learning, computer vision, natural language processing, robotics, predictive analytics, IoT and cloud-edge computing are increasingly integrated into agricultural systems to enhance decision-making, productivity and sustainability. These technologies enable precision farming, crop monitoring, disease detection, forecasting, automation and supply chain optimization, improving efficiency while reducing resource wastage. However, AI adoption remains limited due to high costs, lack of technical skills, data and infrastructure gaps, regulatory uncertainties and concerns about privacy and adaptability. Additional challenges include farmer resistance and the potential loss of traditional agricultural knowledge, highlighting the need for a balanced integration of technology and human expertise. Looking ahead, advances in autonomous systems, multimodal data integration and adaptive learning are expected to make agriculture more resilient, inclusive and sustainable. Overall, AI offers strong potential to improve productivity and strengthen global food security under changing environmental conditions. Continued investment in research, digital infrastructure and capacity building will be essential to realize the full potential of AI for sustainable agricultural development.

Keywords: Artificial intelligence; Agriculture; Precision farming; Machine learning; Deep learning; IoT; Robotics; Predictive analytics; Sustainable agriculture; Smart farming

INTRODUCTION

Agriculture has long been a fundamental activity for human civilization, providing essential sustenance for individuals and communities (Rafael 2023). In many developing countries, it remains the backbone of the economy, with a large share of the population depending on it directly or indirectly.

Over time, farming systems have shifted from traditional subsistence methods to more input-intensive and industrial approaches, largely driven by the green revolution (Evenson and Gollin 2003, Pingali 2012).

While these advancements have significantly increased food production, they have also led to unintended consequences such as soil erosion, excessive reliance on chemical inputs, depletion of water resources, environmental pollution and increased vulnerability to climate change (Tilman et al 2002, Foley et al 2011).

Today, the global agricultural sector is under growing pressure from population growth, climate change and land degradation, all of which threaten long-term food security (Chen 2025). Rapid population increase has intensified demand for food while available farmland continues to shrink, further strained by extreme weather events such as droughts, floods and frosts.

Climate change remains one of the most persistent challenges, reshaping agricultural systems and increasing uncertainty for farmers worldwide (Zhao et al 2017, Seleiman and Kheir 2018). These conditions highlight the urgent need for modern, knowledge-based agricultural strategies that improve efficiency and resilience. Modern agricultural technologies offer promising solutions by optimizing inputs, reducing waste and adapting production systems to environmental stress (Simsek 2025).

In this context, artificial intelligence (AI) has emerged as a transformative technology capable of addressing multiple agricultural challenges simultaneously. Recent advancements in AI have significantly reshaped the agricultural industry, particularly in areas such as precision farming and supply chain management (Arjun 2013).

Technologies like unmanned aerial systems (UAS) are increasingly used for disease detection, yield estimation, growth prediction and weed management. Similarly, internet of things (IoT) sensors combined with AI algorithms are improving soil monitoring and enabling precision irrigation, thereby maximizing resource efficiency (Tsouros et al 2019).

AI refers to the development of machines capable of performing tasks that typically require human intelligence, such as learning, perception and decision-making (Kurzweil 1990). Unlike traditional decision-support systems, AI systems can improve their performance through adaptive learning and can process large volumes of structured and unstructured data in real time (Godfray et al 2010). This capability supports more accurate and timely decision-making in agricultural management. The ability to analyze big data has further advanced precision agriculture, enabling farmers to make informed decisions that improve yields and resource efficiency (Hussein et al 2025).

The integration of AI in agriculture represents a shift from experience-based decision-making to a more data-driven and predictive system. AI applications can improve weather forecasting, monitor soil and crop health using sensors and satellite imagery and optimize irrigation, fertilization and planting schedules. These improvements enhance productivity, reduce waste and strengthen resilience to climate-related stresses (Arshad and Martin 2002). By combining data from weather patterns, soil characteristics, crop stages, remote sensing and historical yields, AI provides farmers with actionable insights for crop selection, planting time, input use, pest management and harvesting strategies (Liakos et al 2018, Kamilaris and Prenafeta-Boldu 2018).

Importantly, AI is not limited to large-scale commercial farming. It is increasingly accessible to smallholder farmers through smartphones, cloud-based platforms, mobile applications and AI-powered advisory systems. These tools provide region-specific recommendations and help bridge the gap between farmers and research institutions. This growing accessibility supports the development of a more inclusive and equitable agricultural system (Karim et al 2025, Foley et al 2011).

In precision farming, AI integrates GPS, IoT sensors, data analytics and machine learning to enable intelligent, data-driven farm management. It optimizes inputs, improves monitoring of soil and crops and enhances sustainability and productivity (Tiwari 2025). AI also aligns closely with the goals of climate-smart agriculture by promoting efficient resource use, reducing dependence on agrochemicals and conserving water resources. As a result, AI is contributing to the development of more sustainable and resilient food systems (Belwal et al 2025). With continued investment from governments, researchers and agri-tech innovators, AI is expected to play a central role in strengthening global food security in the future.

This article, therefore, examines the key components, applications, socioeconomic impacts, limitations and future prospects of AI in agriculture. Overall, it is evident that AI has the potential to transform agriculture by enhancing productivity, improving resource efficiency and empowering farmers in an increasingly uncertain global environment (Wolfert et al 2017, Liakos et al 2018).

Core components of AI

AI is an assemblage of interrelated computing components that work together to imitate certain aspects of human intelligence and support informed decision-making, rather than functioning as a standalone or fully autonomous technology (Wolfert et al 2017). These components enable machines in agricultural systems to observe field conditions, process and interpret large volumes of data, learn from past experiences and take appropriate actions (Liakos et al 2018). The following section explains the basic components of AI.

Data acquisition and sensing systems: Data is the foundation of any AI-powered system. In agriculture, it is collected from multiple sources such as soil sensors, weather stations, satellites, drones, farm machinery and smartphones. This data helps capture key information on crop growth stages, pest activity, temperature, humidity, rainfall, soil moisture, nutrient levels and historical production patterns. Through smart sensors, data analytics and intelligent systems, raw agricultural inputs like soil, water and crop data can be transformed into actionable insights for nutrient management and sustainable production (Dhakal et al 2026).

By integrating digital technologies with biofortification, food safety and decision-support tools, AI and IoT-based systems enable a more nutrition-sensitive and health-oriented approach to agriculture, improving both productivity and public well-being. The IoT and modern sensing technologies also support continuous and real-time farm monitoring. Smart farming combines AI and IoT within cyber-physical systems to enable integrated farm management (Sharma and Shivandu 2024).

AI models can detect field variability and generate precise, site-specific recommendations at high resolution. However, their performance is often affected by challenges such as limited data availability, imbalanced datasets and difficulties in data fusion (Li et al 2025). Ultimately, the effectiveness of AI systems depends heavily on the strength of the sensing infrastructure, as reliable and high-quality data inputs are essential for accurate and meaningful outcomes.

Machine learning algorithms: Machine learning is used to enable computers to perform tasks that humans can carry out more effectively (Arel et al 2010). It allows systems to automatically access data and improve their performance over time through experience. In agriculture, it has become an essential tool that simplifies complex decision-making processes and supports efficient farm management (Benos et al 2021).

Machine learning is a key analytical component of AI, enabling systems to learn from data without explicit programming. It helps identify complex patterns and relationships in agricultural systems, such as links between crop growth, soil conditions and weather patterns. These algorithms are widely applied in irrigation planning, pest detection, disease forecasting and crop yield prediction. Their accuracy improves as more data becomes available, allowing them to adapt effectively to changing environmental conditions. Unlike conventional tools, machine learning systems continuously improve through learning from data over time.

Deep learning and neural networks: Inspired by biological mechanisms of the human brain for processing natural signals, deep learning (DL) has gained significant attention in recent years due to its strong performance in areas such as speech recognition, collaborative filtering and computer vision (Mishra and Gupta 2017).

Today, DL is widely regarded as a key area within machine learning, AI and data science because of its ability to learn directly from large datasets (Sarker 2021). It is based on artificial neural networks, which form its core structure. These networks consist of multiple layers that process information hierarchically, allowing systems to recognize and interpret complex patterns in data.

In agriculture, deep learning has become especially important for image-based applications such as fruit grading, weed detection, plant disease diagnosis and yield estimation. For instance, DL models can detect early stages of plant diseases by analyzing leaf images, enabling timely intervention. This capability also supports automation and advanced image recognition in smart farming systems. Overall, the ability of deep learning to handle large and complex datasets has opened new opportunities for agricultural data analytics and decision-making (Mukherjee et al 2025).

Computer vision: Computer vision is a branch of AI that enables machines to capture, process and interpret visual information from images or videos, allowing them to make decisions or perform tasks in a way that resembles human visual perception through algorithms and mathematical models. It relies on high-quality visual data for accurate analysis and is widely used in areas such as agricultural automation, autonomous driving and medical imaging (Cao et al 2025).

In agriculture, computer vision analyzes images collected from drones, satellites or cameras mounted on farm machinery (Zhang and Kovacs 2012). These systems support crop assessment, detection of nutrient deficiencies, monitoring of crop growth and estimation of biomass. In addition, real-time applications such as precision spraying and robotic weeding use computer vision combined with deep learning algorithms to improve field operations. Similar to how human vision depends on eyes, computer vision systems rely on cameras and other visual sensors to collect and interpret visual data (Chen et al 2020). Overall, this technology improves accuracy and efficiency in farming while reducing the need for manual crop inspection.

Natural language processing (NLP): NLP is a branch of AI that enables machines to understand, interpret and communicate in human language. It supports voice-based and text-based systems that allow farmers to interact with technology in their local languages, ask questions and receive relevant, easy-to-understand responses. By simplifying complex information, NLP makes agricultural knowledge more accessible and practical for end users.

NLP plays a significant role in improving technology adoption among smallholder farmers by overcoming barriers related to literacy and language. As a result, it helps bridge the gap between farmers and expert agricultural knowledge, making decision-support tools more inclusive and user-friendly.

Predictive analytics and decision support systems: Predictive analytics uses historical data, real-time weather conditions, soil information and other relevant variables to forecast future outcomes. In agriculture, it helps estimate how current environmental and farm conditions will influence crop performance and yield. It combines both past and real-time data to support more accurate forecasting, including crop yield prediction, disease outbreaks and pest infestations (https://www.thetatechnolabs.in/blog-posts/ai-in-agriculture-predictive-analytics-for-crop-yield-optimization).

AI-based predictive analytics models are widely used in agricultural decision-making to reduce uncertainty and improve planning. These systems are often integrated with decision support systems (DSS), which translate analytical outputs into practical recommendations for farmers. For example, they may suggest adjustments in irrigation schedules or provide insights on expected water availability, helping farmers take proactive rather than reactive decisions.

DSS is an integrated combination of software and hardware designed to support organizational decision-making processes. It is primarily data-driven, relying on the continuous collection and analysis of relevant information to generate useful insights (Waghmode and Jamsandekar 2014). Overall, predictive analytics and DSS together play a key role in improving farm planning, reducing risks and supporting more informed agricultural decisions.

Robotics and automation systems: The functional basis of this technology in agriculture is robotics, which refers to meaningful actions performed through digital intelligence. In modern farming, routine operations such as planting, weeding, spraying, harvesting and sorting are increasingly carried out by robots and autonomous vehicles. Advanced sensing systems and navigation technologies enable these machines to operate with high precision and efficiency (Kamilaris and Prenafeta-Boldu 2018).

Robotic technology offers several advantages, including higher productivity, timely execution of farm operations and addressing labour shortages, particularly in developing and rural regions. A field crop robot is defined as a mobile, autonomous, decision-making mechatronic system that performs crop production tasks such as soil preparation, seeding, transplanting, weeding, pest control and harvesting under human supervision but without direct manual labour (Lowenberg-DeBoer et al 2020).

Overall, robotics in agriculture enhances efficiency, reduces human workload and supports more precise and automated farming systems.

Cloud computing and edge computing: AI requires significant processing power and data storage capacity. Cloud computing supports the scalability of AI applications by enabling the analysis of large datasets through powerful remote servers. It also offers advanced analytics capabilities, making it suitable for handling complex agricultural data. At the same time, edge computing reduces dependence on continuous internet connectivity by processing data closer to the source, ensuring faster response times and uninterrupted operation in field conditions.

Edge computing brings data processing geographically closer to the user and can function as an intermediate node that distributes computational tasks across multiple devices. A key advantage is that sensitive data can be processed locally without being transmitted to the cloud, enhancing privacy and security. It also reduces data transfer volume, thereby, lowering bandwidth usage and operational costs (Serena et al 2022, Tianqing et al 2022). Edge computing is particularly useful in real-time applications that require low latency, such as industrial and security systems (Qian and Coutinho 2022).

In contrast, cloud computing provides high flexibility in data storage and computing power. Many providers offer pay-as-you-go models, which reduce initial investment costs by charging users based on actual usage.

Cloud platforms also manage hardware maintenance and provide user-friendly interfaces, making advanced services more accessible. Their scalability allows easy expansion of storage and computing resources, even temporarily, which is essential for handling fluctuating workloads (Gutierrez-Torre et al 2022, Shin et al 2022).

Feedback and learning mechanisms: Feedback loops are a fundamental concept in AI that enable continuous learning and adaptation. In machine learning based systems, AI processes data, generates predictions or decisions and then improves its performance by learning from the outcomes. Feedback loops support this process by allowing models to adjust their algorithms based on the difference between predicted and actual results.

This iterative learning mechanism is similar to human learning from experience and is essential for building intelligent systems capable of operating in complex environments (https://www.fastercapital.com/content/Feedback-loops--Feedback-in-Artificial-Intelligence--Learning-Machines--Feedback-in-Artificial-Intelligence.html).

AI systems in agriculture rely heavily on continuous feedback from field data. Over time, models refine their predictions by comparing expected outcomes with real-world results, leading to more accurate and location-specific recommendations. This adaptive learning process improves applications such as disease forecasting, nutrient management and irrigation planning, making AI systems more reliable and better aligned with farmers' needs (Wolfert et al 2017).

AI in agriculture: key areas of application

AI is being applied across every stage of the agricultural value chain, from pre-sowing planning and crop management to post-harvest processing and market integration. By transforming traditional farming into a smart and data-driven system, AI improves precision, increases productivity and promotes sustainability in agriculture (Kamble et al 2020). The following sections discuss the major areas of AI intervention that are reshaping modern agriculture.

Precision farming: One of the most important innovations in modern agriculture is precision farming, which uses AI to support site-specific crop management (Gebbers and Adamchuk 2010, Bongiovanni and Lowenberg-DeBoer 2004). Precision farming combines data from soil sensors, drones, satellite imagery, weather stations and farm machinery to monitor field conditions accurately and guide farming operations. Unlike conventional methods that apply uniform treatments across entire fields, AI enables the application of inputs such as water, fertilizers and pesticides according to the specific needs of different areas within the field. This approach improves resource efficiency, lowers production costs and reduces the environmental impacts associated with excessive chemical use.

AI-powered smart irrigation systems are a major example of precision farming in practice. These systems monitor factors such as soil moisture, evapotranspiration and short-term weather forecasts in real time to determine the exact timing and quantity of water required. By using real-time data for irrigation management, farmers can conserve water, prevent waterlogging and maintain soil health and fertility more effectively. Overall, precision farming enhances productivity while promoting more sustainable agricultural practices.

Crop monitoring and disease detection: AI-based crop monitoring systems use deep learning and computer vision technologies to assess plant health and detect abnormalities at early stages. High-resolution images collected from drones, satellites and smartphone cameras are analyzed to identify signs of diseases, pest infestations, nutrient deficiencies and other physiological stresses, enabling timely and informed interventions (Mohanty et al 2016).

Unlike traditional crop monitoring methods, where action is often taken only after visible damage has occurred, AI systems can detect subtle changes in plant leaves and growth patterns that may not be noticeable to the human eye. Early detection helps reduce crop losses and prevents the spread of diseases and pests. In addition, AI-supported disease diagnosis improves plant protection management by enabling more accurate and targeted interventions, reducing unnecessary chemical use and supporting healthier crop production.

Predictive analytics: Predictive analytics is an important AI tool that helps farmers anticipate future conditions and make informed decisions accordingly (Shamshiri et al 2018). Using machine learning techniques, these systems analyze large datasets that include weather conditions, soil characteristics, crop growth patterns and historical yield records to generate highly accurate forecasts.

The insights produced through predictive analytics support farm planning, crop management and resource allocation. They also assist farmers in making financial and marketing decisions by providing advance estimates of production outcomes and potential market conditions.

In addition, predictive analytics plays a valuable role in managing agricultural risks associated with climate change by reducing uncertainty related to weather variability, pest outbreaks and market fluctuations. Overall, it helps farmers adopt more proactive and resilient farming strategies.

Robotics and automation: Robotics and automation represent one of the most practical applications of AI in agriculture, particularly for labour-intensive and repetitive tasks such as planting, weeding, spraying, trimming, harvesting and grading (Kamble et al 2020). Equipped with computer vision, machine learning and advanced sensor technologies, these systems can move through fields, identify crops and weeds and perform operations with high precision and efficiency.

For example, AI-powered robotic weeders can mechanically remove unwanted plants while protecting crops, reducing the dependence on chemical herbicides. Automation also ensures that farm operations are carried out at the right time, improving overall efficiency and helping address labour shortages in agricultural areas. In horticulture and vegetable production, robotic harvesting systems help reduce post-harvest losses and maintain uniform product quality, thereby, increasing market value and productivity.

Supply chain optimization and market analysis: AI plays a crucial role in agricultural supply chain management by supporting data-driven decision-making and resource optimization (Saxena et al 2023). Its applications extend beyond crop production and are increasingly important in improving the efficiency and reliability of agricultural supply chains. AI systems analyze key data related to production volumes, storage conditions, transportation and market demand to support better planning and coordination across the supply chain.

Effective supply chain management is essential for ensuring the timely delivery of agricultural products to markets while reducing losses caused by overproduction and poor demand forecasting. AI-based forecasting tools help predict market demand more accurately, enabling farmers and distributors to make better production and storage decisions. In addition, AI technologies can support real-time product tracking from farm to consumer, improving traceability, quality control and food safety.

AI also creates opportunities for more direct connections between farmers and consumers, potentially increasing farmers' profits by reducing dependence on intermediaries. Technologies such as machine learning, deep learning and the Internet of Things IoT contribute significantly to demand forecasting, logistics management and efficient resource allocation within agricultural supply chains (Angayarkanni et al 2025). The growing use of AI-driven supply chain systems has influenced not only agriculture and the food industry but also sectors such as manufacturing and the automotive industry (Wang et al 2024).

Comparison of key AI technologies in agriculture: Table 1 provides a summary of fundamental AI technologies and their primary functions in agricultural applications.

Benefits of AI in agriculture

AI offers several benefits in agriculture by improving decision-making, optimizing resource use and promoting sustainable farming practices. The integration of AI technologies helps farmers address productivity challenges while reducing environmental impacts and improving the overall efficiency of agricultural systems. Through data-driven insights and automation, AI supports more precise, resilient and sustainable farm management.

The following sections discuss the major benefits of AI in agriculture in detail.

Enhanced efficiency and productivity: AI enhances agricultural productivity by enabling precision farming, optimizing resource use, automating farm operations and improving crop health monitoring and yield prediction through data-driven decision-making (Hassan et al 2022, 2023, Adinarayana et al 2024, Delfani et al 2024). One of the greatest advantages of AI is its ability to increase production and operational efficiency across agricultural systems.

AI can rapidly process large volumes of data from soil conditions, weather patterns, imaging technologies and historical farm records, tasks that would require much more time using conventional methods. This faster analysis allows farmers to make timely and informed decisions. AI systems also provide recommendations for improving practices such as pest management, fertilizer application, irrigation scheduling and planting density, helping farmers achieve higher yields through more efficient resource management.

In addition, AI-driven technologies and automated machinery perform farm operations with greater precision and fewer errors compared to traditional approaches. By reducing time losses and improving efficiency, AI enables higher agricultural output while using the same or even fewer inputs, ultimately contributing to increased productivity and profitability.

Sustainable resource use: The long-term sustainability of agricultural productivity depends on the efficient management of natural resources and AI plays an important role in achieving this goal. AI-assisted precision farming enables the accurate application of water, fertilizers and herbicides only where and when they are needed. This targeted approach helps reduce environmental pollution, prevent nutrient loss through leaching and minimize the excessive use of agricultural inputs.

AI-controlled systems also optimize water use by considering factors such as crop growth stages, soil moisture levels and weather conditions. In addition, AI supports the cultivation of sustainable and environmentally friendly farming systems by reducing dependence on chemical inputs and improving the resilience of agriculture to changing climatic conditions. Through better resource management and reduced waste, AI contributes to the development of more climate-resilient and sustainable agricultural practices.

Precision agriculture and AI further promote environmental sustainability by optimizing the use of resources such as water, fertilizers and pesticides, thereby, minimizing waste and reducing environmental impacts (Majumder et al 2021). Research also shows that precision agriculture can help lower greenhouse gas emissions by improving resource efficiency and reducing unnecessary input use (Smith et al 2020).

Improved risk management: Agriculture is inherently risky because it depends heavily on weather conditions, biological processes and market fluctuations. AI strengthens agricultural risk management by providing accurate forecasts and early warning systems. AI-based technologies, combined with satellite imagery and predictive analytics, help farmers take preventive action before challenges such

Table 1. Core AI technologies and their functions in agricultural applications

AI technology	Primary function	Agricultural application
Machine learning	Pattern detection and prediction	Yield forecasting; weather risk assessment
Computer vision	Image analysis from drones and sensors	Crop health monitoring; disease/pest identification
Robotics and automation	Performing physical farm tasks autonomously	Weeding, spraying, harvesting, autonomous tractors
Predictive analytics	Forecasting trends based on historical and real-time data	Crop planning; irrigation scheduling
Internet of things (IoT)	Network of connected sensors gathering real-time data	Soil moisture, pH, nutrient monitoring
Natural language processing (NLP)	Communication with farmers	Chatbot advisory systems

as irregular rainfall, pest outbreaks and soil degradation lead to serious losses (Seth 2026).

Machine learning systems analyze large volumes of historical and real-time data to predict disease outbreaks, pest infestations, extreme weather events and yield fluctuations. This early detection enables farmers to adopt mitigation measures before significant damage occurs. For example, weather forecasts can help farmers adjust planting and harvesting schedules, while pest activity alerts support timely intervention and crop protection.

By reducing uncertainty and minimizing potential losses, AI improves the resilience of farming systems and supports more stable agricultural production under changing climatic conditions. In addition, AI-driven solutions help farmers achieve higher efficiency and better economic returns while reducing environmental impacts through more precise and sustainable farm management practices (Murugesan 2024).

Accessibility for smallholder farmers: AI offers a significant opportunity to bridge the knowledge gap between smallholder farmers and agricultural research systems. AI has the potential to transform agricultural production in low- and middle-income countries by improving productivity, strengthening climate resilience and reducing the labour burden on farmers (Anon 2025).

Through tools such as chatbots, mobile applications and digital advisory platforms, farmers can receive timely and relevant information directly on their mobile devices. Many of these systems are designed to be accessible even for users with low literacy levels, often using voice-based or simplified interfaces that are suitable for rural contexts. As a result, AI platforms help expand access to agricultural knowledge by providing expert guidance on crop selection, pest and disease management and market trends.

Overall, AI contributes to more inclusive and equitable agricultural development by ensuring that high-quality, research-based information is more widely accessible to smallholder farmers, supporting better decision-making and improved livelihoods.

Challenges and limitations

AI has the potential to significantly transform agriculture; however, several challenges continue to limit its effective implementation (Anon 2022). Despite its promise, the adoption of AI in agriculture is still constrained by financial, technological and infrastructural barriers, particularly for smallholder farmers. The main challenges affecting the successful deployment of AI in agriculture are discussed in the following sections.

High initial investment: The high cost of advanced technologies is one of the major barriers to the adoption of AI in agriculture. Implementing AI requires substantial technological infrastructure, which is often unaffordable for many farmers, particularly in developing countries. This includes investments in sensors, robotics, data analytics systems, drones, automated machinery, smart irrigation systems and AI-based software platforms (Sharma et al 2022, Qazi et al 2022).

In addition to the initial investment, farmers also face ongoing costs such as installation, maintenance and data storage, which further increase the financial burden. As a result, small and medium-scale farmers often find these technologies beyond their economic capacity. The lack of adequate financial support mechanisms, such as loans, subsidies and insurance schemes for AI-based agricultural tools, further discourages adoption. Consequently, the use of AI in agriculture remains largely concentrated in large-scale commercial farming systems, limiting its wider accessibility and slowing its adoption across the broader agricultural sector.

Requirement of technical expertise and training: A major concern in the adoption of AI in agriculture is the lack of technical proficiency among farmers and agricultural workers to effectively use AI-based tools. As a result, workforce training remains a critical barrier to successful implementation (Morota et al 2018).

Although technological advancements in agriculture are increasing, their adoption has been relatively slow, mainly due to limited digital literacy and insufficient technical expertise among farmers (https://m.dailyhunt.in/news/india/english/analytics+insight-epaper-anycinst/challenges+and+limitations+of+ai+in+agriculture-newsid-n696312081).

Successful use of AI requires a certain level of digital skills, including the ability to operate AI-enabled tools, interpret data outputs and integrate recommendations into routine farming practices.

However, many rural communities lack access to adequate training programmes, extension services and technical support, which leads to hesitation and reluctance in adopting these technologies. This resistance is often stronger among older farmers and those with limited experience in using digital platforms, particularly when AI systems appear complex or difficult to understand.

Without strong capacity-building initiatives, the benefits of AI in agriculture cannot be fully realized. Therefore, farmer-friendly system design, continuous training and ongoing technical support are essential to ensure effective and widespread adoption.

Data availability and connectivity constraints: Another key challenge in the adoption of AI in agriculture is the complexity of data management. AI systems generate and depend on vast amounts of data, which can be difficult to collect, store, process and analyze effectively. This also requires farmers and stakeholders to develop adequate skills in data handling and interpretation (Idoje et al 2021).

High-quality and reliable datasets are essential for developing effective AI models. However, in many agricultural settings, especially in developing countries, the availability of accurate farm data is limited. Factors such as the lack of sensors, weak record-keeping practices and minimal digital data generation significantly restrict data availability. In addition, reliable internet connectivity is crucial for the functioning of many AI-based systems.

Unstable electricity supply and poor internet infrastructure further hinder the adoption of cloud-based AI solutions. In regions with low connectivity or frequent outages, the effectiveness of AI-generated recommendations is reduced, as timely data transmission and access become difficult. As a result, the benefits of AI in agriculture are often limited in such environments, slowing down its widespread implementation.

Data privacy and security concerns: The rapid advancement of AI in agriculture has the potential to outpace existing regulatory frameworks, creating challenges for the safe and responsible use of these technologies. A major barrier to the widespread adoption of data-driven agricultural systems is the lack of clarity regarding data ownership, privacy and security, as well as the legal interpretation of agricultural data (Wolfert et al 2017).

As AI systems increasingly collect and process sensitive farm-level information, concerns about data misuse, unauthorized access and exploitation by private entities have become more prominent. These concerns often make farmers hesitant to share their data, limiting the effectiveness of AI applications. This situation is further complicated by the absence of well-defined regulations and policies governing the use, storage and sharing of agricultural data. Strengthening legal frameworks is, therefore, essential to build trust and encourage wider adoption of AI in agriculture.

Limited adaptability across regions: AI models in agriculture are often designed for specific crops, climates or geographical regions, which can lead to inconsistent performance when applied in different agro-ecological contexts. If these models are not properly localized and validated, their recommendations may become inaccurate or irrelevant, ultimately reducing farmer confidence in the technology.

The effectiveness and trustworthiness of AI in agriculture depend largely on its ability to adapt to local conditions. However, agricultural environments vary significantly in terms of crop types, soil characteristics, topography and weather patterns, even across nearby farms. This high level of variability makes it challenging for AI models trained on limited or region-specific datasets to perform reliably in new or diverse settings (Shrestha 2024).

Resistance to change: Farmers' resistance to change has long been a barrier to the adoption of new agricultural technologies. Many farmers are often concerned about the reliability and complexity of emerging tools, while others are reluctant to disrupt established farming practices that they have relied on for years. These concerns can slow down the acceptance and integration of AI in agriculture.

However, pilot projects, demonstration farms and real-world case studies that clearly show the practical benefits of these technologies have been effective in reducing skepticism. Involving farmers directly in the development, testing and refinement of AI solutions can also improve their relevance, usability and cultural suitability. Such participatory approaches help build trust and encourage wider adoption of AI-based agricultural innovations (Mallinger and Baeza-Yates 2024).

Concern about the loss of agricultural knowledge in the age of AI: AI can significantly enhance agricultural productivity; however, it may also reduce the farmer's direct role in decision-making by transferring key responsibilities to automated systems. As AI becomes more deeply integrated into farming practices, there is a risk that farmers and agricultural workers may gradually lose traditional skills and experiential knowledge essential for effective crop and livestock management.

This concern becomes more serious in the context of potential system failures or cyber security threats. Over-reliance on AI-based decision-making systems may weaken farmers' ability to interpret subtle environmental signals such as changes in soil conditions, weather patterns or pest activity, which are often identified through long-term experience and intuition (Sparrow et al 2021). As a result, maintaining a balance between technological assistance and human expertise is essential to ensure resilience and informed decision-making in agriculture.

The future of AI in agriculture

AI is expected to play an increasingly transformative role in shaping the future of agriculture, where farms evolve into intelligent and adaptive ecosystems. In this vision, AI moves beyond its current role of assisting human decision-making and gradually becomes integrated into fully autonomous farming systems that can monitor, analyze and respond to field conditions in real time.

Future agricultural systems are likely to rely heavily on edge computing to ensure rapid, localized decision-making even in areas with limited internet connectivity. At the same time, robotics will work in coordination with AI to carry out essential farm operations such as planting, irrigation, weeding and harvesting. These systems will continuously learn from field experiences, improving their performance and efficiency over time through adaptive learning mechanisms.

A key advancement in this direction is multimodal data fusion, where diverse data sources such as satellite imagery, drone-based monitoring, soil sensors, weather data and even genetic crop information are integrated to generate a comprehensive understanding of agricultural systems. By combining these multiple data streams, AI models can produce more accurate predictions related to crop growth, pest outbreaks, yield estimation and resource requirements.

As these systems become more sophisticated and data-rich, their predictive accuracy and reliability are expected to improve significantly through continuous self-learning. This will also enhance their ability to generalize across different crops, climates and geographical regions, making them more useful for diverse farming contexts, including smallholder systems in developing countries.

With increased innovation, collaboration and technological advancement, AI-driven agriculture has the potential to create a more inclusive, resilient and efficient farming ecosystem. Ultimately, it can support the development of agricultural systems that are not only 'smart' and productive but also sustainable, adaptive and economically viable for future generations.Top of Form

CONCLUSION

Artificial intelligence is emerging as a transformative force in agriculture, offering innovative solutions to long-standing challenges related to productivity, resource management and sustainability. By integrating technologies such as machine learning, computer vision, IoT, robotics and predictive analytics, AI enables more precise, efficient and data-driven farming practices. These advancements support improved crop monitoring, optimized input use, enhanced risk management and better supply chain coordination, ultimately contributing to higher productivity and reduced environmental impact.

However, the widespread adoption of AI in agriculture is still constrained by several challenges, including high costs, limited technical expertise, inadequate infrastructure, data scarcity, regulatory gaps and concerns over privacy and adaptability. Social factors such as resistance to change and the potential erosion of traditional farming knowledge further complicate implementation. Addressing these challenges requires targeted policy support, capacity building, improved digital infrastructure and farmer-centric design of AI tools.

In the future, AI is expected to evolve into more autonomous and adaptive agricultural systems supported by edge computing, robotics and multimodal data integration. These developments will enhance decision-making accuracy and system resilience across diverse agro-ecological regions. If implemented responsibly and inclusively, AI has the potential to create a smarter, more sustainable and equitable agricultural system that strengthens global food security while supporting farmers' livelihoods in a changing climate.

REFERENCES

Adinarayana S, Raju MG, Srirangam DP, Prasad DS, Kumar MR and Veesam SB 2024. Enhancing resource management in precision farming through AI based irrigation optimization. In: How machine learning is innovating today's world: a concise technical guide (A Dey, S Nayak, R Kumar and SN Mohanty, Eds), Scrivener Publishing, pp 221-251; doi: 10.1002/9781394214167.ch15.

Angayarkanni A, Sheshasaayee A, YuJie Z and Ohmsakthi vel R, 2025. Agricultural process optimization and supply chain management enhancing sustainable agriculture through AI technology. Journal of Information Systems Engineering and Management **10(32s):** 421-432. doi: 10.52783/jisem.v10i32s.5319.

Anonymous 2022. In brief to the state of food and agriculture 2022: leveraging automation in agriculture for transforming agrifood systems. Food and Agriculture Organization of the United Nations, Rome, Italy.

Anonymous 2025. Harnessing artificial intelligence for agricultural transformation. World Bank. (https://www.worldbank.org/en/topic/agriculture/publication/harnessing-artificial-intelligence-for-agricultural-transformation) (Retrieved: 11.03.2026)

Arel I, Rose DC and Karnowski TP 2010. Deep machine learning – a new frontier in artificial intelligence research. IEEE Computational Intelligence Magazine **5(4):** 13-18; doi: 10.1109/MCI.2010.938364.

Arjun KM 2013. Indian agriculture-status, importance and role in Indian economy. International Journal of Agriculture and Food Science Technology **4(4):** 343-346.

Arshad MA and Martin S 2002. Identifying critical limits for soil quality indicators in agro-ecosystems. Agriculture, Ecosystems and Environment **88(2):** 153-160; doi: 10.1016/S0167-8809(01)00252-3.

Belwal T, Huang R and Zhao H 2025. Editorial: Defining the role of artificial intelligence (AI) in the food sector and its applications. Frontiers in Nutrition **12:** 1596699; doi: 10.3389/fnut.2025.1596699.

Benos L, Tagarakis AC, Dolias G, Berruto R, Kateris D and Bochtis D 2021. Machine learning in agriculture: a comprehensive updated review. Sensors **21(11):** 3758; doi: 10.3390/s21113758.

Bongiovanni R and Lowenberg-DeBoer J 2004. Precision agriculture and sustainability. Precision Agriculture **5:** 359-387; doi: 10.1023/B:PRAG.0000040806.39604.aa.

Cao Z, Sun S and Bao X 2025. A review of computer vision and deep learning applications in crop growth management. Applied Sciences **15:** 8438; doi: 10.3390/app15158438.

Chen J, Zhang M, Xu B, Sun J and Mujumdar AS 2020. Artificial intelligence assisted technologies for controlling the drying of fruits and vegetables using physical fields: a review. Trends in Food Science and Technology **105:** 251-260; doi: 10.1016/j.tifs.2020.08.015.

Chen X 2025. The role of modern agricultural technologies in improving agricultural productivity and land use efficiency. Frontiers in Plant Science **16:** 1675657; doi: 10.3389/fpls.2025.1675657.

Delfani P, Thuraga V, Banerjee B and Chawade A 2024. Integrative approaches in modern agriculture: IoT, ML and AI for disease forecasting amidst climate change. Precision Agriculture **25:** 2589-2613; doi: 10.1007/s11119-024-10164-7.

Dhakal M, Banerjee M and Pandey KK and Seniya C 2026. AI and IoT are no longer limited to high-tech labs but are improving nutrition-focused agricultural farming. Discover Food **6:** 69; doi: 10.1007/s44187-025-00777-w.

Evenson RE and Gollin D 2003. Assessing the impact of the green revolution, 1960 to 2000. Science **300(5620):** 758-762; doi: 10.1126/science.1078710.

Foley JA, Ramankutty N, Brauman KA, Cassidy ES, Gerber JS, Johnston M, Mueller ND, O'Connell C, Ray DK, West PC, Balzer C, Bennett EM, Carpenter SR, Hill J, Monfreda C, Polasky S, Rockstrom J, Sheehan J, Siebert S, Tilman D and Zaks DPM 2011. Solutions for a cultivated planet. Nature **478:** 337-342; doi: 10.1038/nature10452.

Gebbers R and Adamchuk VI 2010. Precision agriculture and food security. Science **327(5967):** 828-831; doi: 10.1126/science.1183899.

Godfray HCJ, Beddington JR, Crute IR, Haddad L, Lawrence D, Muir JF, Pretty J, Robinson S, Thomas SM and Toulmin C 2010. Food security: the challenge of feeding 9 billion people. Science **327(5967):** 812-818; doi: 10.1126/science.1185383.

Gutierrez-Torre A, Bahadori K, Baig S-u-R, Iqbal W, Vardanega T, Berral JL and Carrera D 2022. Automatic distributed deep learning using resource-constrained edge devices. IEEE Internet of Things Journal **9(16):** 15018-15029; doi: 10.1109/JIOT.2021.3098973.

Hassan M, Kowalska A and Ashraf H 2023. Advances in deep learning algorithms for agricultural monitoring and management. Applied Research in Artificial Intelligence and Cloud Computing **6(1):** 68-88.

Hassan M, Malhotra K and Firdaus M 2022. Application of artificial intelligence in IoT security for crop yield prediction. ResearchBerg Review of Science and Technology **2(1):** 136-157.

https://m.dailyhunt.in/news/india/english/analytics+insight-epaper-anycinst/challenges+and+limitations+of+ai+in+agriculture-newsid-n696312081%20 (Retrieved: 20.03.2026)

https://www.fastercapital.com/content/Feedback-loops--Feedback-in-Artificial-Intelligence--Learning-Machines--Feedback-in-Artificial-Intelligence.html (Retrieved: 19.03.2026)

https://www.thetatechnolabs.in/blog-posts/ai-in-agriculture-predictive-analytics-for-crop-yield-optimization. (Retrieved: 22.03.2026)

Hussein JB, Workneh TS, Kassim A, Ntsowe K, Melesse SF and El-Mesery HS 2025. A review on the impact of big data analytics in transforming agricultural practices, food processing and preservation strategies. Applied Food Research **5(2):** 101234; doi: 10.1016/j.afres.2025.101234.

Idoje G, Dagiuklas T and Iqbal M 2021. Survey for smart farming technologies: challenges and issues. Computers and Electrical Engineering **92:** 107104; doi: 10.1016/j.compeleceng.2021.107104.

Kamble SS, Gunasekaran A and Gawankar SA 2020. Achieving sustainable performance in a data-driven agriculture supply chain: a review. International Journal of Production Economics **219:** 179-194; doi: 10.1016/j.ijpe.2019.05.022.

Kamilaris A and Prenafeta-Boldu FX 2018. Deep learning in agriculture: a survey. Computers and Electronics in Agriculture **147:** 70-90; doi: 10.1016/j.compag.2018.02.016.

Karim S, Hussain K, Alvi MB, Rahu MA, Kaloi MA and Haleem H 2025. Artificial intelligence in sustainable smart agriculture: concepts, applications and challenges. Transactions on Computer Sciences **13(1):** 307-342; doi: 10.21015/vtcs.v13i1.2151.

Kurzweil R 1990. The age of intelligent machines. MIT Press, Cambridge, MA, pp 579-580.

Li X, Cheng Y, Moller C and Lee J 2025. Data issues in industrial AI systems: a meta-review and research strategy. Computers in Industry **173:** 104361; doi: 10.1016/j.compind.2025.104361.

Liakos KG, Busato P, Moshou D, Pearson S and Bochtis D 2018. Machine learning in agriculture: a review. Sensors **18(8):** 2674; doi: 10.3390/s18082674.

Lowenberg-DeBoer J, Huang IY, Grigoriadis V and Blackmore S 2020. Economics of robots and automation in field crop production. Precision Agriculture **21:** 278-299; doi: 10.1007/s11119-019-09667-5.

Majumder D, Akhter J, Mandal A, Roy R, Bhatt R and Hossain A 2021. Precision input management for minimizing and recycling of agricultural waste. In: Input use efficiency for food and environmental security (R Bhatt, RS Meena and A Hossain, Eds), Springer, Singapore, pp 567-603; doi: 10.1007/978-981-16-5199-1_19.

Mallinger K and Baeza-Yates R 2024. Responsible AI in farming: a multi-criteria framework for sustainable technology design. Applied Sciences **14(1):** 437; doi: 10.3390/ app14010437.

Mishra C and Gupta DL 2017. Deep machine learning and neural networks: an overview. IAES International Journal of Artificial Intelligence **6(2):** 66-73; doi: 10.11591/ijai.v6.i2.pp66-73.

Mohanty SP, Hughes DP and Salathe M 2016. Using deep learning for image-based plant disease detection. Frontiers in Plant Science **7:** 1419; doi: 10.3389/fpls.2016.01419.

Morota G, Ventura RV, Silva FF, Koyama M and Fernando SC 2018. Big data analytics and precision animal agriculture symposium: Machine learning and data mining advance predictive big data analysis in precision animal agriculture. Journal of Animal Science **96(4):** 1540-1550; doi: 10.1093/jas/sky014.

Mukherjee S, Begum S, Mondal S, Mukhopadhyay AK, Chakraborty S and Chakraborty D 2025. Deep learning in agriculture: challenges and opportunities – a comprehensive review. African Journal of Biomedical Research **28(1S):** 2397-2415; doi: 10.53555/AJBR.v28i1S.6701.

Murugesan S 2024. Leveraging AI to foster climate resilient and sustainable agriculture. Amplify **37(7):** 35-42.

Pingali PL 2012. Green revolution: impacts, limits and the path ahead. Proceedings of the National Academy of Sciences of the United States of America **109(31):** 12302-12308; doi: 10.1073/pnas.0912953109.

Qazi S, Khawaja BA and Farooq QU 2022. IoT-equipped and AI-enabled next generation smart agriculture: a critical review, current challenges and future trends. IEEE Access **10:** 21219-21235; doi: 10.1109/ACCESS.2022.3152544.

Qian W and Coutinho RWL 2022. Performance evaluation of edge computing-aided IoT augmented reality systems. In: Proceedings of the 18th ACM International Symposium on QoS and Security for Wireless and Mobile Networks: Q2SWinet '22, 24-28 October 2022, Montreal, QC, Canada, pp 79-86; doi: 10.1145/3551661.3561371.

Rafael BM 2023. The importance of agricultural development projects: a focus on sustenance and employment creation in Kenya, Malawi, Namibia, Rwanda and Uganda. Journal of Agricultural Chemistry and Environment **12(2):** 152-170; doi: 10.4236/jacen.2023.122013.

Sarker IH 2021. Deep learning: a comprehensive overview on techniques, taxonomy, applications and research directions. SN Computer Science **2:** 420; doi: 10.1007/s42979-021-00815-1.

Saxena K, Jakhete MD, Kumari L, Jain M, Mane A and Karthik HP 2023. Optimizing agricultural supply chains with machine learning algorithms. Journal of Advanced Zoology **44(S-2):** 3146-3156. doi: 10.53555/jaz.v44iS2.1546.

Seleiman MF and Kheir AM 2018. Saline soil properties, quality and productivity of wheat grown with bagasse ash and thiourea in different climatic zones. Chemosphere **193:** 538-546; doi: 10.1016/j.chemosphere.2017.11.053.

Serena L, Zichichi M, D'Angelo G and Ferretti S 2022. Simulation of hybrid edge computing architectures. In: Proceedings of the 2021 IEEE/ACM 25th International Symposium on Distributed Simulation and Real Time Applications: DS-RT '21, 27-28 September 2021, Valencia, Spain, pp 1-8; doi: doi: 10.1109/DS-RT52167.2021.9576121.

Seth A 2026. AI at the core of agri transformation. Hindustan Times, 11 May 2026.

Shamshiri RR, Weltzien C, Hameed IA, Yule IJ, Grift TE, Balasundram SK, Pitonakova L, Ahmad D and Chowdhary G 2018. Research and development in agricultural robotics: a perspective of digital farming. International Journal of Agricultural and Biological Engineering **11(4):** 1-14; doi: 10.25165/j.ijabe.20181104.4278.

Sharma K and Shivandu SK 2024. Integrating artificial intelligence and internet of things (IoT) for enhanced crop monitoring and management in precision agriculture. Sensors International **5:** 100292; doi: 10.1016/j.sintl.2024.100292.

Sharma V, Tripathi AK and Mittal H 2022. Technological revolutions in smart farming: current trends, challenges and future directions. Computers and Electronics in Agriculture **201:** 107217; doi: 10.1016/j.compag.2022.107217.

Shin H, Koo D and Hur J 2022. Secure and efficient hybrid data deduplication in edge computing. ACM Transactions on Internet Technology **22(3):** 80; doi: 10.1145/3537675.

Shrestha A 2024. Multi-temporal UAV remote sensing combined with machine learning for estimating cotton yield. PhD Dissertation, Mississippi State University, Mississippi State, United States; URL: https://scholarsjunction.msstate.edu/td/6350.

Simsek O 2025. Harvesting sustainability: innovations and practices in modern agriculture. Green Technologies and Sustainability **3(3):** 100192; doi: 10.1016/j.grets.2025.100192.

Smith P, Soussana J-F, Angers D, Schipper L, Chenu C, Rasse DP, Batjes NH, van Egmond F, McNeill S, Kuhnert M, Arias-Navarro C, Olesen JE, Chirinda N, Fornara D, Wollenberg E, Alvaro-Fuentes J, Sanz-Cobena A and Klumpp K 2020. How to measure, report and verify soil carbon change to realize the potential of soil carbon sequestration for atmospheric greenhouse gas removal. Global Change Biology **26(1):** 219-241; doi: 10.1111/gcb.14815.

Sparrow R, Howard M and Degeling C 2021. Managing the risks of artificial intelligence in agriculture. NJAS: Impact in Agricultural and Life Sciences **93(1):** 172-196; doi: 10.1080/27685241.2021.2008777.

Tianqing Z, Zhou W, Ye D, Cheng Z and Li J 2022. Resource allocation in IoT edge computing via concurrent federated reinforcement learning. IEEE Internet of Things Journal **9(2):** 1414-1426; doi: 10.1109/JIOT.2021.3086910.

Tilman D, Cassman KG, Matson PA, Naylor R and Polasky S 2002. Agricultural sustainability and intensive production practices. Nature **418(6898):** 671-677; doi: 10.1038/nature01014.

Tiwari NR 2025. Application of artificial intelligence in agriculture. International Journal of Geography, Geology and Environment **7(8):** 9-14.

Tsouros DC, Bibi S and Sarigiannidis PG 2019. A review on UAV-based applications for precision agriculture. Information **10(11):** 349; doi: 10.3390/info10110349.

Waghmode ML and Jamsandekar PP 2014. Decision support systems and its applications in different sectors: Literature review. International Journal of Advance Research in Computer Science and Management Studies **2(1):** 110-115.

Wang W, Chen Y, Zhang T, Deveci M and Kadry S 2024. The use of AI to uncover the supply chain dynamics of the primary sector: building resilience in the food supply chain. Structural Change and Economic Dynamics **70:** 544-566. doi: 10.1016/j.strueco.2024.05.010.

Wolfert S, Ge L, Verdouw C and Bogaardt M-J 2017. Big data in smart farming – a review. Agricultural Systems **153:** 69-80; doi: 10.1016/j.agsy.2017.01.023.

Zhang C and Kovacs JM 2012. The application of small unmanned aerial systems for precision agriculture: a review. Precision Agriculture **13:** 693-712; doi: 10.1007/s11119-012-9274-5.

Zhao C, Liu B, Piao S, Wang X, Lobell DB, Huang Y, Huang M, Yao Y, Bassu S, Ciais P, Durand J-L, Elliott J, Ewert F, Janssens IA, Li T, Lin E, Liu Q, Martre P, Muller C, Peng S, Penuelas J, Ruane AC, Wallach D, Wang T, Wu D, Liu Z, Zhu Y, Zhu Z and Asseng S 2017. Temperature increase reduces global yields of major crops in four independent estimates. Proceedings of the National Academy of Sciences **114(35):** 9326-9331; doi: 10.1073/pnas.1701762114.

***How to cite this article*:** Sharma S 2026. Harnessing artificial intelligence for sustainable and data-driven agriculture. Int J Farm Sci 16(2-3): 72-85; doi: 10.5958/2250-0499.2026.00026.9.