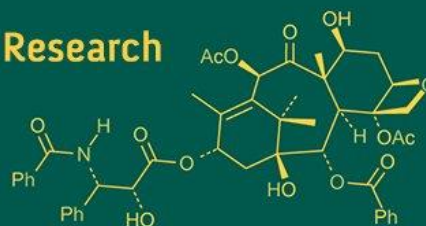


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AI-driven agricultural economics and farm decision support systems

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Abstract

AI is bringing transformational change to agricultural economics by facilitating data-driven decision-making in farm production, resource management, financial planning, and marketing. The combination of the recent advances in machine learning (ML), deep learning (DL), computer vision, Internet of Things (IoT), remote sensing (RS), robotics, cloud computing, and big data analytics has enabled Farm Decision Support Systems (FDSS) for enhancing crop management, input-use efficiency, decreasing production cost, and increasing profit. AI-based systems also facilitate crop choice, irrigation and nutrient management, pests and diseases forecasting, yield prediction, price forecasting and market analysis, helping to reduce production risk under climate and market uncertainties. Novel technologies such as generative AI, Large Language Models, digital twins, blockchain, reinforcement learning and explainable AI further enhance decision accuracy, automation and supply chain transparency. AI is also advancing climate-smart agriculture through precision input management, diminished use of resources and GHG emissions, and enhanced climate variability resiliency. Nevertheless, adoption is still limited by lack of digital infrastructure, poor data quality, high cost of implementation, limited technical capacity, algorithmic transparency and data governance issues, particularly in developing countries. This review focuses on and recent advances in AI-enhanced agricultural economics and FDSS, highlighting key technologies, economic model applications, implementation challenges, ethical issues, and future research directions. To summarize, responsible AI deployment can enable economically feasible, climate-resilient, environmentally sustainable agriculture, promote food security, and advance evidence-based agricultural policy making.

Keywords: Artificial Intelligence, Agricultural Economics, Farm Decision Support Systems, Precision Agriculture, Smart Farming, Decision Analytics

1. Introduction

Agriculture is being redefined by digitalization, facilitated by technological development and widespread adoption of artificial intelligence (AI), data analysis, and precision agriculture technologies. At the same time, agricultural production is becoming more complex due to climate change, resource depletion, labor shortage, market volatility, and increasing food demand. The traditional experience-based and generalized advice type of management may not be sufficient to solve these intertwined problems. AI has the ability to process massive amounts of heterogeneous agricultural data in real time, resulting in better and more accurate decisions. Through the application of data collected from remote sensing, drones, IoT sensor, weather stations, cloud computing, and GIS (Geographic Information Systems), AI facilitates improved crop planning, irrigation, nutrient management, pest and disease management, harvesting, and monetary decisions leading to increased productivity, resource-use efficiency, profitability, and environmental sustainability (Ditcharoen *et al.*, 2023; Mahmood *et al.*, 2025) [18, 43].

Recent progress in machine learning, deep learning, reinforcement learning, computer vision, generative AI and Large Language Models (LLMs) further reinforced the support for agricultural decisions. Intelligent Farm Decision Support Systems (FDSS) can assimilate agronomic, climatic, environmental, and economic factors to deliver real-time, site-specific recommendations; meanwhile, production efficiency and sustainable resource management are enhanced by such technologies as Variable Rate Technology (VRT), IoT-based monitoring, smart irrigation and autonomous machinery (Saiz-Rubio and Rovira-Mas, 2020)

[55]. Weather forecasting, yield and market prediction, climate-risk assessment, and adaptive management are some of the climate-smart agriculture activities supported by AI, which also helps supply chains, insurance, credit assessment and other economic decisions (Jha *et al.*, 2019) [29]. Nevertheless, high prices, lack of infrastructure, limited technical capacity, scattered landholding patterns, interoperability problems and concerns about data privacy and algorithm transparency continue to be significant obstacles, emphasizing the necessity for enabling infrastructure, policies, capacity development and responsible AI governance.

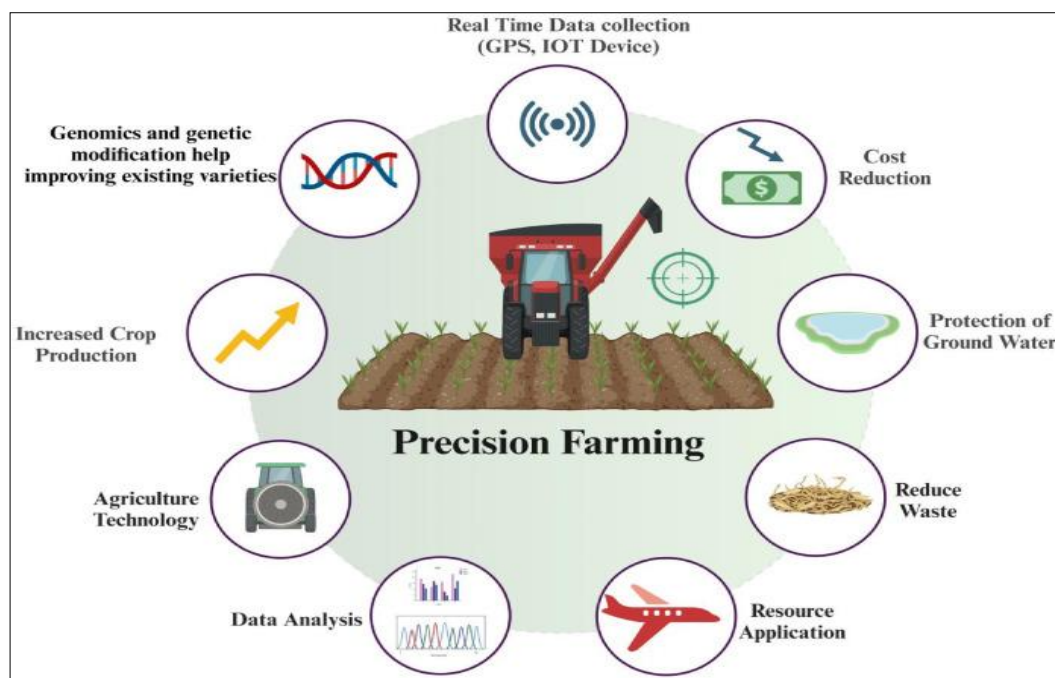
2. Evolution of Agricultural Economics in the Era of Artificial Intelligence

Agricultural economics has undergone a significant transformation from traditional production and resource allocation theoretical frameworks to smart and data-based decision support systems (Tantalaki *et al.*, 2019) [65]. Farm management decisions historically were informed by record keeping, observation in the field, experience of the producer and generalized recommendations, which often did not adequately account for spatial or temporal variability within agricultural production. The development of precision agriculture brought in new technologies like Global Positioning Systems (GPS), Geographic Information Systems (GIS), remote sensing, and Variable Rate Technology (VRT) for site-specific management, and improved application of agricultural inputs (Sharma, 2023) [57]. These developments paved the way for the application of artificial intelligence in agricultural economics (Wolfert *et al.*, 2017) [72].

The rapid growth of digital farming has also contributed to this evolution through the mass adoption of IoT sensors and other technologies, for example drones, satellite images, automated weather stations, cloud computing or mobile-based agriculture solutions (Dhal *et al.*, 2024) [16]. These technologies produce constant streams of large volumes of real-time agronomic, environmental, climatic, and economic

data that are beyond the capabilities of traditional statistical methods. AI addresses these limitations by leveraging machine learning and sophisticated predictive analytics to discover intricate interactions between production, market, and environmental variables, which results in improved and timelier economic decision-making (Knizia *et al.*, 2025) [38]. Contemporary agricultural economics is more and more dependent on AI and its scope is expanding towards predicting yields, estimating costs of production, optimizing inputs, forecasting prices, evaluating risks, and analyzing profitability (Assimakopoulos *et al.*, 2024; Redouane *et al.*, 2025) [4, 52]. Deep learning-based crop monitoring and disease diagnosis from images reinforcement learning-based management strategies that adapt to dynamic field environments are continually evolving. Explainable AI enhances transparency by delivering interpretable suggestions which lead to an increased trust of the farmers in the AI-enabled decision making. More recent developments have seen the introduction of generative AI and Large Language Models into the agricultural advisory space through intelligent conversational systems that simplify sophisticated scientific knowledge into actionable ad farm advice (Choi *et al.*, 2025) [12].

At the same time, Farm DSSs have been turned into digital platforms that integrate agronomic, climatic, environmental and financial data to enable strategic, tactical and operational decision at the farm management level (Gerasymchuk *et al.*, 2026) [25]. New era technologies such as digital twins, blockchain, autonomous robotics, cloud-based analytics enable more accurate production planning, transparent supply chain, and resource utilization optimization. As a result, agricultural economics now is in a transformative phase from being a descriptive economic analysis to a predictive and prescriptive intelligence, which derives farm profit maximization solution based on data while facilitating climate resilience, environmental sustainability, and long-term food and nutritional security (Tyagi and Tiwari, 2025) [66].



Source: Aijaz *et al.*, 2025 [2]

3. Fundamentals of AI and Farm Decision Support Systems

Artificial intelligence (AI) is a computational system that can learn from data, identify patterns, make predictions and assist in decision making with limited human intervention (Jaboob *et al.*, 2024) ^[28]. In farming, AI is now compiling data from satellites, drones, IoT sensors, weather stations, equipment, soil tests and market databases to deliver actionable, hyperlocal advice. Instead of static advisory systems, AI can evolve by learning from data to adapt to changing environment of production (Hossain *et al.*, 2025) ^[26].

Farm Decision Support Systems (FDSS) are information technology-based systems intended to support the farmer and other stakeholders in taking agronomic and economic decisions in the farm production process. Contemporary FDSS integrate agroclimatic and environmental conditions with economic information to suggest the best crop varieties, sowing dates, irrigation schedules, fertilizer dosages, pest and disease control strategies, harvesting dates, and marketing alternatives. These systems have the effect of reducing risk, minimizing input use, maximizing operating efficiency, and increasing farm profitability (Achille and Velamuri, 2026) ^[1].

A standard AI-powered FDSS may include four key elements: data acquisition, data processing, decision analytics and information delivery (Panda, 2021) ^[47]. Data are gathered by IoT sensors, remote sensing, drones, weather stations, and market information systems. Machine learning and predictive models processed these datasets to detect patterns, predict outcomes, and provide suggestions for management. Ultimately, the information is provided to the end user through mobile applications, web portals, or cloud-based solutions, delivering decision in real time. With the rapid development of AI based-technologies, FDSS are now considered essential for precision farming, climate change adaptation and sustainable agriculture management (Khwidzhilli and Ijatuyi, 2026) ^[37].

4. AI Technologies Used in Agricultural Economics

Artificial intelligence encompasses a broad range of computational technologies that improve agricultural decision-making by analyzing complex datasets and generating predictive insights. These technologies support production planning, economic optimization, market forecasting, and resource management, thereby enhancing both productivity and profitability.

4.1 Machine Learning

ML is now commonly employed in the agricultural economics to process large datasets, find patterns and make predictions. Data from weather stations, satellites, IoT smart sensors, drones and farm management systems facilitate the prediction of crop yields as well as cost and profitability analysis, market forecasting, resource utilization, and risk assessment. Supervised, unsupervised and ensemble techniques are capable to model intricate nonlinear relations within the space of climatic, agronomic and economic variables, providing more confidence under a dynamic scenario. Therefore, ML leads to better use of resources, productivity, cost-effectiveness, and financial sustainability (Domingues, 2022; Storm *et al.*, 2020; Vuppapapati, 2021) ^[19, 61, 69].

4.2 Deep Learning

Deep learning (DL), as an important sub-discipline of machine learning, employs multilayer neural networks to achieve high accuracy for the analysis of large-scale and complex data. Its image-processing properties can be extended to precision farming and include monitoring crop health, disease diagnosis, detecting weeds, finding fruits, judging maturity, grading quality, and estimating yield based on fruit, leaf, flower, and stem images and those collected by drone, satellite, hyperspectral, and smartphone. By directly learning the useful features, DL enables fast and accurate decisions, as well as automated surveillance and robotic applications. Hence, it can enhance the production efficiency and economic benefit by reducing labor input and mistakes (Learning *et al.*, 2023; Zheng *et al.*, 2023) ^[40, 74].

4.3 Generative AI and Large Language Models

Generative AI and Large Language Models (LLMs) are novel agri-advisory tools that comprehend and produce human-like language. They help farmers by responding to their technical questions, interpreting research, giving farm management advice, and offering tailored recommendations influenced by the weather, soil, crops, and market. Multilingual AI assistants democratize access to agricultural knowledge, and LLMs empower extension professionals via report generation, translation, training materials, and live advisory services. Through enabling effective knowledge sharing and digital extension, such technologies have the potential to enhance support to farmers and farmer decision-making (De Clercq *et al.*, 2024; Li *et al.*, 2026) ^[13, 41].

4.4 Reinforcement Learning

Reinforcement learning (RL) is a sophisticated AI methodology that enables algorithms to learn optimal management policies by interacting with the farming system and being informed by the outcomes of the decisions. Different from traditional predictive models, RL is a sequential decision-making process which enables the system to find a sequence of actions to achieve the greatest long-term productivity and economic benefits. In precision irrigation scheduling, fertilizer management, greenhouse climate control, autonomous agricultural machinery, robotic harvesting, and adaptive pest management, reinforcement learning is gaining popularity in agriculture. As more field data are generated, RL algorithms adapt and update their advice such that intelligent and dynamic farm management is possible in an evolving climatic and production scenario (Khanna *et al.*, 2024; Liu, 2025) ^[35, 42].

4.5 Explainable AI

Explainable Artificial Intelligence (XAI) provides a more complete understanding of the processes behind the predictions or recommendations, notably the input features used in the decision-making process. Even though many complex AI models function as "black boxes", not allowing users to know the logic behind results. XAI maps this constraint by disaggregating the underlying factors that drive each recommendation and in the process building greater confidence with farmers, researchers, financial institutions, and policymakers. Transparent AI systems can promote technology uptake, enhance accountability, facilitate regulatory compliance, and mitigate risks associated with biased or erroneous predictions. With the

growing presence of AI in agriculture decision-making, explainability will continue to be crucial for responsible and reliable use (Yang *et al.*, 2023; Dipu *et al.*, 2026) ^[73, 17].

4.6 Computer Vision

Computer vision facilitates the automation interpretation of the agricultural images/videos for precision crop monitoring and management. When combined with drones, satellites, robots, smartphones and hyperspectral imaging, it identifies nutrient and water stress, pests, diseases, weeds, fruit maturity and harvest readiness. Post-harvest, it can be used for fruit counting, crop phenotyping, quality grading and sorting; it decreases manual scouting, enhances early detection, harvesting efficiency and production management. Therefore, computer vision plays an indispensable role in AI-based precision agriculture (Dhaka *et al.*, 2021; Karanam *et al.*, 2023) ^[14, 33].

4.7 Internet of Things (IoT) and Edge AI

The Internet of Things (IoT) combines agricultural sensors and equipment, weather stations, drones, and irrigation systems into a connected system to monitor soil, crop, and environmental conditions in real time (Duguma and Bai, 2024) ^[20]. Edge AI processes this data at or near the data source, eliminating communication latency, bandwidth consumption, and dependency on cloud connectivity. IoT combined with Edge AI can intervene quickly with irrigation and nutrition management, greenhouse automation, livestock monitoring, and air control, thus reducing resource use and enhancing efficiency (Khan *et al.*, 2023; Renda, 2024) ^[34, 53].

4.8 Digital Twins

Digital twins are digital constructs of agricultural systems that integrate live sensor data, simulation models, and artificial intelligence to mirror field conditions and forecast field performance. They can model crop growth, soil processes, irrigation, machinery operations, climate impacts and farm finances under what-if scenarios. By assessing the management concepts in advance of use, digital twins contribute to the optimal use of inputs, minimizing risks, enhancing production scheduling, and providing assistance for financial decisions. They are also considered to be more and more promising for precision farming, climate adaptation, sustainability assessment and long-term farm management (Verdouw *et al.*, 2021; van Evert *et al.*, 2026) ^[68, 67].

5. AI Applications in Agricultural Economics

Artificial intelligence has become a key driver of agricultural economics by enabling data-driven decision-making across the entire agricultural value chain. By integrating agronomic, climatic, financial, and market information, AI helps optimize resource allocation, improve profitability, reduce production risks, and enhance the overall efficiency of farming systems. Its applications extend from production planning and financial management to market forecasting, supply chain optimization, and sustainable resource utilization (Weersink *et al.*, 2018) ^[70].

5.1 Production Economics

Artificial intelligence enhances the production economics by ensuring the optimal use of land, labour, water, fertilizers, pesticides, and machinery. Machine learning uses

soil, weather, crop growth and yield data, as well as management information to suggest the most profitable cropping system and site-specific input application. Decision support based on AI is used to support decisions related to crop and variety selection, planting dates, irrigation and nutrient management, as well as pest and disease forecasting. These applications lead to higher efficiency in use of inputs, reduced production costs and environmental load, increased productivity and improved farm profit and farm sustainability (Talaviya *et al.*, 2020) ^[64].

5.2 Farm Financial Management

Artificial intelligence contributes to managing farm finances with smart budgeting, cash flow projection, investment scheduling, and analysis of profitability. By combining production records, input and labor costs, machinery costs, weather information, and market prices, AI applications allow farmers to monitor performance and financial status in real-time and help in predictive financial analysis. They enable you to evaluate risk, investment, compare alternative enterprises, and identify efficiency gains. In turn, AI enables informed business planning, strengthens financial stability, and fosters sustainable farm management (Miller *et al.*, 2023) ^[44].

5.3 Cost-Benefit Analysis

Artificial intelligence enhances cost-benefit calculations by combining information on production as it occurs, weather forecasts, market information, availability of labor, and risk factors. Using predictive modeling and scenario simulations, the AI models also compare technologies, irrigation systems, nutrient regimens, mechanization alternatives, and crop types. These studies provide estimates of production costs, returns, risk to the investment, and the benefit-cost ratio across a range of situations and have been shown to support sound decisions by farmers, the agribusiness community, and policy makers regarding technology use, investment, and agriculture policy while mitigating economic uncertainty (Antle *et al.*, 2017; Olutumise, 2026) ^[3, 46].

5.4 Yield and Profit Forecasting

AI provides precise prediction of crop yield and farm profitability through the integration of information on weather, soil, crop growth, satellite and UAV images, and historical production. Along with production costs, labor and input needs, the AI generates preliminary estimates for farm income and profitability when market prices are available. These projections inform production planning, marketing, storage, and financial choices, and help mediate risks associated with climate, pests, and market volatility (Carolan, 2024; Khin and Lee, 2026) ^[10, 36].

5.5 Market Intelligence

Based on commodity prices, consumers demand, weather activities, transportation cost, trade, policies and market trend, the intelligence systems driven by AI can examine and then predict the opportunities and demands. They are also used to analyze consumer preferences and supply and demand and identify profitable markets, buyers and selling periods. This enhances the efficiency of marketing, reduces uncertainty, empowers farmers in bargaining, and may lead

to an increase in farm income (Pauw *et al.*, 2023; Ladhar *et al.*, 2023) [49, 39].

5.6 Price Forecasting

Agricultural commodity prices vary by production, demand, weather, transport, government policies, and international trade. The AI-based prediction models combine historical price trends and weather data with supply demand relationships, trade patterns and macroeconomic indicators to enhance price prediction. Forecast accuracy thus allows farmers to make better decisions on harvesting, storage, transportation, procurement and marketing, reducing financial risks, increasing bargaining power, and enhancing farm profitability (Farh *et al.*, 2026; Sun *et al.*, 2023; Basha *et al.*, 2026) [23, 62, 6].

5.7 Supply Chain Optimization

Artificial intelligence (AI) contributes to agricultural supply chain management through demand forecasting, logistics, transport, inventory, warehousing, and quality of products. AI minimizes processing delay, storage loss, and postharvest decay and computer vision is used for quality grading; intelligent logistics optimize delivery routes and warehouse utilization. Traceability, transparency and food safety are more securely established through integration with blockchain. Such applications contribute to lower operating costs, increased market efficiency, added value of products, and more competitive agriculture businesses (Ivanov, 2023; Dhal and Kar, 2024; Kanyepe *et al.*, 2025) [27, 15, 32].

5.8 Crop Insurance

AI is revolutionizing agricultural insurance with the fast evaluation of crop damages, risk modeling, premium calculation and claims procedure automation. Machine learning processes satellite and drone imagery, weather data, and remote sensing information to determine damages

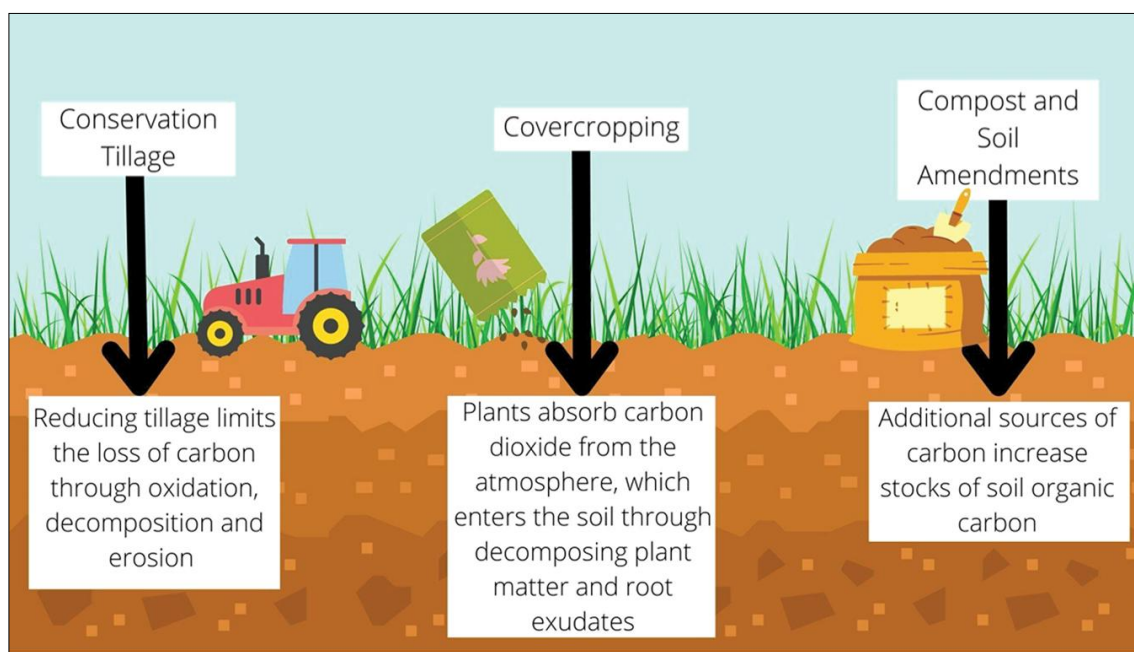
caused by droughts, floods, pests, diseases, and more. AI increases claim speed and transparency, reduces fraud, and facilitates objective compensation. Predictive risk models also help design tailored insurance products and appropriate premium levels that enhance risk management and delivery of financial resources to farmers in a timely manner (Benami *et al.*, 2021; Prakash and Saravanan, 2023; Werulkar and Pande, 2025) [7, 50, 71].

5.9 Credit Risk Assessment

AI enhances agricultural credit evaluation by processing farm outputs, financial statements, weather-related risks, repayment patterns, market behaviour, digital transactions, and satellite imagery. Analysis with AI enables more precise, data-driven risk analysis, which leads to more efficient lending and reduced defaults when compared to traditional methods. Besides, it has the potential to enable tailor-made financial products and increase access to institutional credit for smallholders with scant financial histories, thereby fostering investment in advanced technologies and sustainable practices (Fuster *et al.*, 2022; Sun *et al.*, 2025; Singh and Mritunjay, 2024) [24, 63, 58].

5.10 Carbon Markets

AI is opening up new avenues in climate-smart agriculture via carbon trading and payments for ecosystem services. It can be used to calculate estimates for emissions of greenhouse gases and track soil carbon sequestration as well as to quantify carbon credits by integrating satellite imagery, remote sensing, IoT sensors, field data, and predictive models. AI also enhances the business of carbon crediting, monitoring, verification, certification, and transparent credit trading. These applications can also promote conservation agriculture, agroforestry, cover cropping, and minimum tillage while generating additional sources of income to the farmers (Smith *et al.*, 2020; Satapathy *et al.*, 2026) [60, 56].



Source: <https://net.fft.org.tw/smartnetzero/news.php?act=view&id=326>

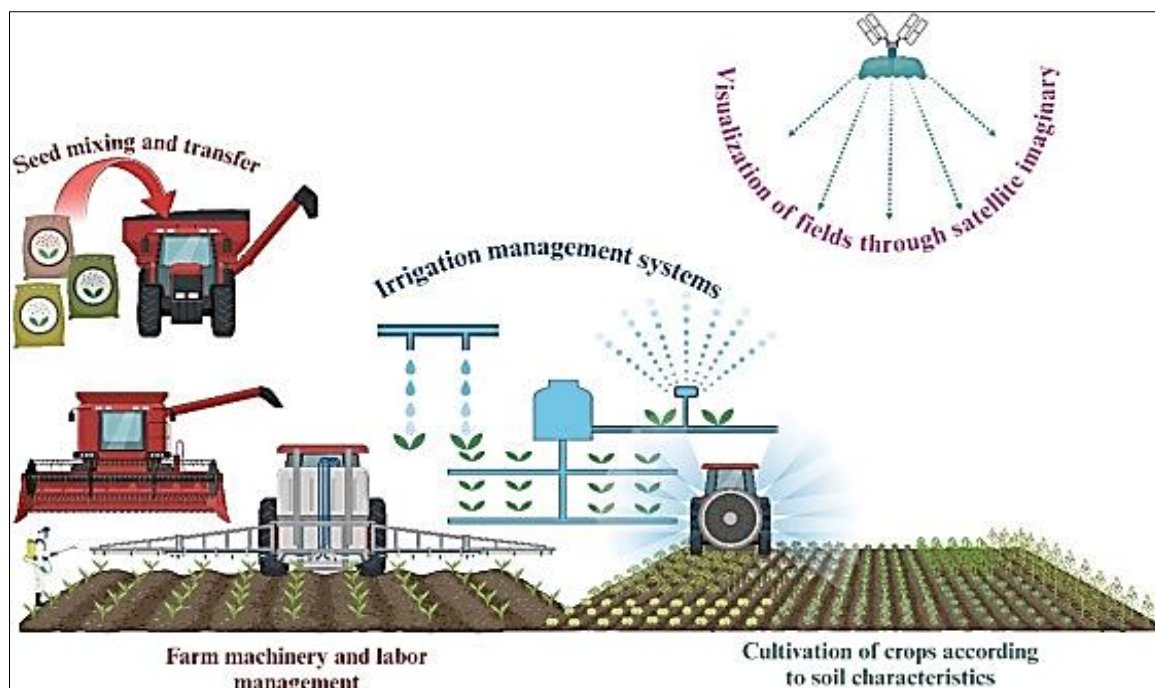
5.11 Precision Input Management

Precision input management is a major economic application of AI in modern agriculture. AI uses IoT

sensors, satellite images, drones, weather information, soil information, crop models and GIS to decide the amount, time and place of irrigation, fertilizer, pesticide and other

inputs to be applied. Variable Rate Technology (VRT) allows site-specific application at varying rates according to crop requirements and field variation while minimizing over- and under-application. Real-time surveillance facilitates prompt actions that contribute to improved

resource-use efficiency, decreased production cost, minimized environmental impact, enhanced productivity and profitability, and sustainable development of agro-ecosystems (Botero-Valencia *et al.*, 2025) ^[9].



Source: Zia-ur-Rehman *et al.*, 2025 ^[76]

6. AI-Driven Farm Decision Support Systems

AI-based Farm Decision Support System (FDSS) merges the aspects of artificial intelligence, agronomic, climatic, environmental and economic information to enable the farm management to be evidence-based. These sources of information are integrated by these systems to offer real-time recommendations on crop choice, sowing dates, irrigation scheduling, fertilizer application, pest and disease handling, harvesting, and selling. Unlike conventional advisory systems, AI-powered FDSS continuously learn from new data, improving the accuracy and reliability of recommendations over time (Eastwood *et al.*, 2022) ^[21].

Modern Farm Decision Support Systems (FDSS) utilize machine learning, predictive analytics, cloud computing, and mobile applications to assess alternative management scenarios and recommend decisions that are best economically. The integration with Geographic Information Systems (GIS) and remote sensing also makes site-specific management feasible considering field heterogeneity. As a result, AI-based decision support systems can increase resource-use efficiency, decrease production costs, risk, farm profit and is environment friendly sustainable agricultural practices (Sishodia *et al.*, 2020) ^[59].

7. Integration with Precision Agriculture

Precision agriculture, based on the integration of GPS, GIS, remote sensing, drones, IoT devices, and Variable Rate Technology (VRT), constitutes the technological enabler for AI-based farm management. These datasets are processed by AI to track growth of crops, soil fertility, moisture status, nutrient availability, and occurrence of pests with fine spatial and temporal granularity. This allows a site-specific use of irrigation water, fertilizers, and

pesticides based on the real needs of the crops instead of uniform field applications (Saha *et al.*, 2025) ^[54].

Autonomous tractors, robotic sprayers, intelligent irrigation systems and harvesting machines guided by Artificial Intelligence (AI) contribute among others to greater operational efficiency by reducing labour dependency and enhancing resource utilization. Persistent watching and prediction-based investigation bring about early identification of crop stress, leading to timely actions that increase productivity and decrease the exposure to environmental contaminants. Hence, AI integration with precision agriculture contributes to economically efficient, climate-resilient and sustainable farming systems (Awais *et al.*, 2025) ^[5].

8. Climate-Smart Farm Decision Support

Climate variability has heightened unpredictability in agricultural production, thus making rational decision support indispensable for adaptation to climate. AI combines historical weather data, climate models, satellite observations and real-time data from sensors and ground stations to predict droughts, floods, heat stress, frost events, and pest outbreaks. These predictions allow farmers to modify planting dates, use climate-resilient crop cultivars, manage water efficiently and take timely crop protection measures (Mohan *et al.*, 2025) ^[45].

AI plays a role in climate change mitigation through enhanced fertiliser recommendations, better irrigation management and energy use, which lead to lower emissions of greenhouse gases from agricultural production. Digital climate advisory services deliver climate-smart, site-specific advice that enhance farm resilience, increase resource-use efficiency and promote climate-smart agriculture

development amid growing environmental variability (Pasha Mohammed *et al.*, 2025) ^[48].

9. AI for Smallholder Farming

Smallholder farmers contribute significantly to the world's food production, but they are often constrained by a lack of technical knowledge, access to finance, and extension services. AI-based mobile apps and digitized advisories platforms are filling these gaps, offering cost-effective, real-time advisories on crop management, weather, pest diagnosis, fertilizer application and market prices in local languages. These innovations are designed to empower smallholders to make decisions based on data, without needing to be highly technical (Fabregas *et al.*, 2019) ^[22].

AI also promotes financial inclusion through digital credit scoring, crop insurance, and farmer-centric mobile-banking services. Weather extremes and pest outbreak early warning systems mitigate production risks, and market intelligence supported by AI enables farmers to identify good marketing opportunities. With the growth of digital infrastructure, AI has the potential to bring about substantial improvements in productivity, income and livelihood security for smallholder farmers (Quarshie *et al.*, 2025) ^[51].

10. Challenges and Limitations

However, the application of artificial intelligence (AI) in agricultural economics is limited due to a number of technical, economic, and infrastructural barriers, despite its great promise. Adoption is also limited by high cost of investment in equipment that incorporates AI, by poor internet connectivity, by unreliable electricity, and by insufficient digital infrastructure, especially for small farmers in developing countries. Further, artificial intelligence systems require data of high quality, which is standardized, and available in near real-time; however, data on agricultural production is often fragmented, inconsistent and heterogeneous when obtained from different sources, such as satellites, Internet of Things (IoT) sensors, weather stations, and market databanks, which negatively affects the precision of decision support based on artificial intelligence (Junior *et al.*, 2024) ^[31].

Limited digital literacy, lack of technical knowledge, insufficient extension services and farmer education also impede the pace of AI adoption. Concerns about data privacy, cybersecurity, transparency of algorithms, interoperability, and data ownership also decrease user confidence and responsible use. Tackling these issues through enhanced digital infrastructure, capacity building, explainable AI, robust data governance, and enabling policies will be key to realizing the broad-based and sustainable utilization of AI in agricultural economics.

11. Ethical, Legal and Policy Issues

The growth of AI in agriculture has raised significant ethical, legal, and policy issues. Ethical deployment of AI is also an issue of transparency, fairness, accountability and inclusiveness, to make sure that the benefits of technology reach all farmers, no matter the size of the farm, where it is located, or the status of the farmer. Algorithmic bias resulting from unrepresentative datasets may generate inaccurate recommendations for certain regions or farming systems, potentially widening existing inequalities in agricultural development (Jobin *et al.*, 2019) ^[30].

Data governance is another critical concern. With sensors, drones, machinery, and farm management platforms, farmers are producing an ever-growing wealth of digital information, yet clear guidelines on data ownership, privacy, sharing, and commercial use are still lacking in several countries. Developing secure data protection structures is necessary to protect farmers rights while promoting responsible innovation and collaboration with technology developers, researchers, and government bodies.

Increasing use of autonomous machinery, AI-assisted advisory systems and automated decisions also poses legal challenges in terms of liability, responsibility and regulatory control. Governments need to establish standards for the validation, quality assurance, certification, and safety of AI-based applications in agriculture to enable reliable and transparent use in the field. Investments from the public shoulder in digital infrastructure, open-data schemes, research collaboration, and farmer capacity enhancement will further accelerate equitable AI adoption and support sustainable agriculture development (Birner *et al.*, 2021) ^[8].

12. Future Research Directions

Future research should be directed towards the establishment of robust, explainable and scalable AI systems that integrate agronomic, environmental, climatic and economic data in decision-support platforms. Advances in Generative AI, LLMs and multimodal AI will bring more personalized and interactive advisory services, farmers will get location-specific recommendations through natural language interfaces. Enhancing the multilingual capabilities of AI systems will also contribute to the strengthening of digital extension services, especially in developing countries (Zhu *et al.*, 2025) ^[75].

Converging AI with digital twins, Internet of Things (IoT), 5G, edge computing, robotics, and blockchain will result in increasingly automated and smart farm systems. Digital twins will be used to model crop growth, resource use and economic performance under alternative management practices for strategic planning and climate adaptation. Traceability enabled through blockchain combined with AI analytics will enhance the transparency of the supply chain, food safety and consumers trust (Casino *et al.*, 2021) ^[11].

Future AI research should also focus on climate-smart agriculture, carbon accounting, ecosystem services valuation, and sustainable resource management. Sophisticated predictive models for climate risk, greenhouse gas emissions, soil carbon sequestration, and biodiversity will underpin environmentally responsible policies for agriculture. Moreover, the combination of AI with socio-economic models will enhance at the farm level investment planning, rural development and agricultural policy analysis (Junior *et al.*, 2024) ^[31].

Collaborative research between universities, government agencies, private technology companies, extension organizations, and farmers will be critical to creating accessible, transparent, and producer-focused AI applications. Standardized datasets, open-source AI frameworks, and international cooperation will further accelerate innovation while ensuring equitable access to digital agriculture technologies worldwide.

13. Conclusion

Artificial intelligence is revolutionizing agricultural economics towards a predictive and data-informed science

through the application of machine learning, IoT, remote sensing, computer vision, robotics, and advanced analytics. Intelligent Farm Decision Support Systems (IFDSS) for production, resource and financial management, market predictions, and input use brings about better farm productivity, profit, and farm stability. Newer technologies such as Generative AI, LLMs, digital twins, XAI, blockchain, and autonomous vehicles contribute further to decision-making and supply chain efficiency. Nevertheless, adoption is constrained by poor infrastructure, high costs, unreliable data, low levels of digital literacy, and fears about privacy and cybersecurity. Hence, there is need to ensure enabling policies, digital infrastructure, harmonized data, capacity development and multi-stakeholder engagement to harness the potential of AI for sustainable, climate-resilient and cost-effective agriculture.

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