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From Aridity To Agility: AI-Driven Organisational Diagnostics For Scaling Controlled-Environment Agribusinesses

Salam Hamd Abudabeel
Email: Sabudabeel@gmail.com

Abstract
Agriculture and agribusiness had been using traditional methods till recently. The developments regarding AI applications in agriculture prompted many of them to adopt AI in various operations of agriculture and agribusiness. Considerable research has been done on this aspect. This qualitative PRISMA review aimed to evaluate the status of research in this respect. Google Scholar was used to identify the relevant papers, and the PRISMA process flow was used to screen and select the most appropriate papers based on some inclusion and exclusion criteria. This resulted in the final selection of 25 papers for this review. Considering that AI applications transform the current agricultural production systems into agile production systems, this review provided much information on how various AI and other technologies contribute to such a transformation. Production is the first stage of agribusiness. At the local level, AI applications transform agriculture into sustainable food production. At the global level, it is concerned with global food availability and security. Apart from production, AI addresses product supply chains, post-harvest processing and marketing through market intelligence, to predict price and volume of arrivals in markets. AI chatbots recommend actions for agribusiness based on these predictions. All these apply to farmers who market their products themselves and large agribusiness firms. However, unless governments intervene with appropriate policies and strategies, a digital divide between the two will limit the access of AI technologies by small farmers. Some limitations of this review and some recommendations for research and practice have been given.
Keywords: *AI, IoT, ML, DL, drones, robots, arid practices, agile practices, agriculture, farming, agribusiness, controlled environment.*

INTRODUCTION

The term "From Aridity to Agility" describes using AI-driven organisational diagnostics to enhance agility and scalability in controlled environment agribusinesses, transforming challenges into opportunities through data-driven insights. AI allows them to improve efficiency, optimise resources, make informed real-time decisions, and adapt to changing conditions. It turns operational inefficiencies (aridity) into adaptive capabilities (agility). Thus, their growth becomes sustainable.

AI application in a controlled environment of agribusiness facilitates early problem detection, supply chain resilience and strategic innovations. The transition from aridity (constraints of resource scarcity, operational issues, etc) to agility (adaptability, responsiveness, growth) can be helped by AI.

This simple qualitative PRISMA review aims to evaluate the status of research in this area. The paper is organised as follows. The next section describes the Methodology used to identify and select papers and data integration for this review. The individual papers are described in the Results section. The findings of the review are synthesised and interpreted in the Discussion section. The limitations of this review, conclusions and suggestions for further research and practice follow to end the paper.

METHODOLOGY

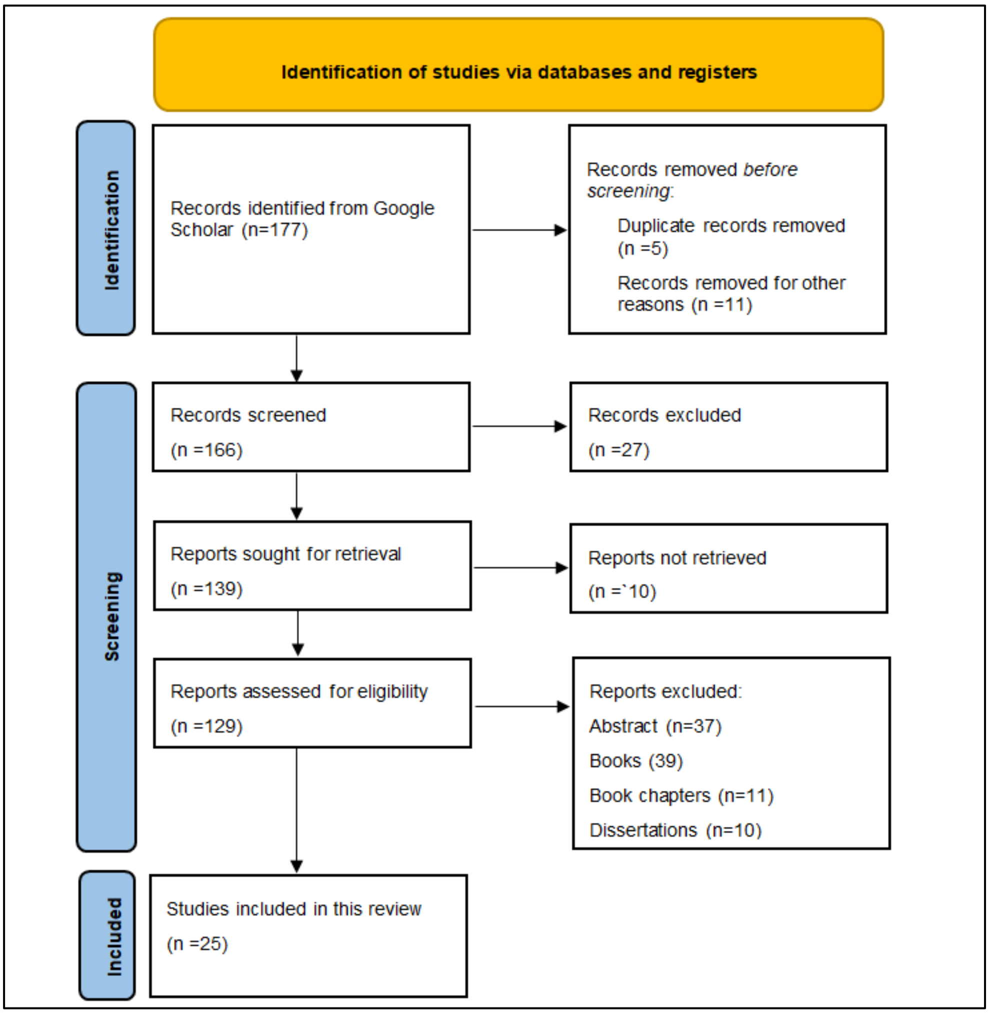
Google Scholar was searched to identify the relevant papers using search terms within the review topic. The identified papers were screened and selected using the PRISMA flow process based on certain inclusion and exclusion criteria given in Table 1. The process resulted in the final selection of 25 papers for this review.

Table 1 *Inclusion and exclusion criteria*

Inclusion criteria	Exclusion criteria	Remarks
Only full-text papers	Abstracts	Abstracts may not contain all the required information.
Papers in English	Other languages	Even the best translation may not be distortion-free.
Published during 2020-2025	Earlier years	To reflect the recent trends.
	Books, chapters	Full-texts considered, if available.

	Dissertations	Guided research
	Editorials, comments, etc	Not considered a research paper.
	Inadequate citation details	Cannot be used.

Figure 1 *PRISMA*



RESULTS

Sudha et al. (2025) noted that Scrum and Kanban aspects of agility contribute to flexibility, continuous improvement, rapid responses to rapid changes in the business environment, decision making and resilience. They enhance competitiveness, risk management, and exploitation of market opportunities to drive the commercialisation of agribusiness. Technological advancements like precision agriculture, controlled environment agriculture, IoT, AI and blockchain facilitate the transition of agribusiness from aridity to agility. Mechatronics and robotics are two technologies used in precision agriculture, which is now a major agribusiness trend. In mechatronics, AI and machine learning algorithms are used. Robots are used for planting, weeding, pest control, harvesting, and crop health monitoring (Dey, et al., 2025). One risk in agribusiness is the disruption of the grain supply chain. Once this happens, production levels in controlled environment agribusiness need to be regulated. Therefore, the resilience of the grain supply chain is important. Integrating emerging technologies within broader socioeconomic development efforts can significantly strengthen supply-chain resilience. Notable examples include blockchain systems, digital transformation initiatives and advancements in artificial intelligence. A triangular framework of conflicting events was employed to represent complex scenarios and extract nodes for the Bayesian network. Next, the scenario was segmented based on scene descriptions, enabling the construction of a scene stream and the derivation of an event network, which serves as the foundation for building the Bayesian network structure. Subsequently, expert insights and Dempster-Shafer (D-S) evidence theory were integrated to determine the network parameters and establish the Bayesian model. Finally, using

2022 drought data from the Yangtze River Basin in China, critical nodes within the grain supply chain were identified, and a phased strategy was proposed to enhance its resilience (Zhang & Zhou, 2025).
Pest attacks can affect production in controlled environment agribusiness. If the occurrence of specific pests in the area can be predicted, efficient pest management strategies can be devised. Using habitat suitability modelling, Holuša and Kaláb (2023) identified areas suitable for the occurrence of *Gryllotalpa gryllotalpa* in the Czech Republic. The main explanatory variables were air temperature, humidity, and soil type. The authors used the machine learning model, Maxent, for this purpose.
Land models help to understand and predict terrestrial processes, including agriculture. Dagon, Sanderson, Fisher, and Lawrence (2020) developed an ML method to globally fine-tune selected parameters of the Community Land Model version 5 (CLM5), using data on carbon and water flows. The focus was on parameters that influence key biophysical processes like energy exchange, water movement, and carbon absorption. To identify the most relevant parameters, sensitivity analyses were done, and objective metrics were used to rank their influence and distinguish their spatial effects. Next, a set of varied parameter combinations was created and trained feed-forward neural networks to mimic CLM5 outputs based on these inputs. The networks were calibrated using global averages of annual carbon and water flux variations. Their accuracies were tested with validation and out-of-sample checks, and applied interpretation tools like feature importance and partial dependence. Finally, the trained models efficiently estimated globally optimal parameter values, outperforming manual tuning and expanding beyond the limited scope of single-site studies.
A report of the World Economic Forum (WEF, 2025) observed that AI provides solutions to the problems (low productivity, fragmented landholdings, limited access to finance and the growing impacts of climate change), reducing the potential of Indian agriculture. A three-pillar framework was proposed for this purpose. It consisted of an "enable" pillar anchoring the role of governments as primary stakeholders in establishing foundational systems, policies, strategies, and institutional arrangements for AI integration into all operations in agriculture. The "create" pillar focuses on driving innovation, where start-ups and innovators collaborate and co-develop AI solutions with research institutions. The "deliver" pillar is about ensuring that the AI solutions reach the farmers through effective extension systems. Feedback loops should inform any refinement required. AI can help in crop planning, advise on crop varieties, inputs planning, incentives planning, farm operations, post-harvest operations and marketing. In all these applications, use cases need to be integrated, all stakeholders need to be involved and cross-cutting basic elements. The use cases are satellite-based crop monitoring, crop variety selection, drone-based field analysis, weather forecasting, AI chatbots to advise farmers, decision support systems, variable rate application of inputs, precision irrigation management, automated farm machinery, pest and disease control, soil and nutrient management, post-harvest management, market access and price forecasting, and agricultural finance and insurance. The datasets required are digital land records, crop calendar and yields, soil health data, satellite imagery, real-time market data, agricultural market network, import-export volumes, historical purchase prices of crops, production and consumption data, weather data, irrigation maps, storage networks, warehouse details, commodity profile, defects and pest images. The report ends with recommendations to the government, start-ups, industry, and for research.
Chen et al. (2025) observed that Controlled Environment Agriculture (CEA) presents a promising avenue for sustainable food production in the face of climate change, resource limitations, and rapid urbanisation. Yet, the complexity of managing CEA systems, driven by the dynamic interaction of environmental factors and the need for multiscale integration, poses significant challenges. The integration of artificial intelligence (AI) is increasingly recognised as a transformative approach to navigating these complexities, fostering innovation and operational efficiency within sustainable food systems. In recent years, research on AI applications in CEA has surged, reflecting both technological progress and heightened interest in intelligent agricultural solutions. Central to this advancement is machine learning, which facilitates automated climate regulation, optimised yield outcomes, and data-informed decision-making. This review synthesises key AI-driven applications, including climate forecasting, yield prediction, disease identification, and intelligent control systems, all of which contribute to enhanced resource use and crop resilience. Despite these advancements, several hurdles persist. The development of more sophisticated models, access to high-quality datasets, and strategies to mitigate implementation uncertainties remain critical for realising the full potential of AI in CEA.
Niranjan et al. (2025) developed an AI-enabled framework that integrates IoT-based sensor networks, climate analytics, and machine learning algorithms to facilitate climate-responsive decision-making in crop management. This architecture synthesises real-time field inputs, such as soil moisture, temperature,

and satellite imagery, with weather forecasts and historical climate data to predict crop yields and irrigation requirements. Using a representative dataset, which includes synthetic climate-crop interactions, the authors demonstrated that incorporating climate variables significantly enhances predictive accuracy. For instance, a baseline model relying solely on soil parameters yields low performance ($R^2 \approx 0.21$), whereas the climate-informed model achieves a substantially higher accuracy ($R^2 \approx 0.72$). The system generates practical recommendations, including adaptive irrigation scheduling and fertiliser optimisation, enabling farmers to better manage climate risks and improve productivity. Experimental findings affirm the value of climate-aware AI models in advancing precision agriculture.

A review by Raza et al. (2023) noted that AI offers transformative solutions to key challenges in agriculture by enhancing efficiency and productivity across multiple domains, including crop and livestock monitoring, irrigation optimisation, pest and disease prediction, and the development of climate-resilient crop varieties. This paper examined the diverse applications and persistent challenges of AI in precision agriculture. Leveraging machine learning algorithms and predictive modelling, AI technologies enable the analysis of extensive climate, soil, and crop datasets to support climate-smart farming practices. These tools generate accurate forecasts and actionable recommendations for precision irrigation, nutrient management, pest and disease surveillance, and yield estimation. By optimising input use, minimising waste, and lowering environmental impact, AI contributes significantly to resource-efficient agriculture. Despite its promise, the adoption of AI faces barriers such as limited data quality and availability, technical skill gaps, and financial constraints. Nonetheless, harnessing AI's capabilities can accelerate the transition toward sustainable, resilient agricultural systems-advancing food security, improving resource stewardship, and mitigating the effects of climate change.

Zidan and Febriyanti (2024) explored the transformative potential of AI, particularly machine learning and deep learning methodologies, in advancing climate adaptation strategies to improve agricultural outcomes. By integrating AI with climatological datasets, the research aims to anticipate and mitigate the adverse effects of climate variability on crop yields. The models employed analyse historical climate patterns in conjunction with crop performance data, drawing on variables such as temperature, precipitation, soil moisture, and crop genetics. Trained on these multidimensional datasets, the AI models demonstrate strong predictive capabilities across diverse climatic scenarios and generate tailored adaptation strategies that significantly enhance yield performance. As such, these tools offer valuable decision support for farmers and agricultural policymakers, enabling proactive, climate-aligned interventions. The findings highlight AI's capacity to convert complex data into actionable insights, reinforcing its role in promoting resilient, data-driven agricultural practices and contributing to the broader advancement of climate-smart agricultural science.

A book by Lal and Mishra (2025) investigates the transformative convergence of artificial intelligence (AI) and agriculture, examining how emerging technologies can be strategically applied to build sustainable and resilient food systems. In response to escalating global pressures, including climate change, population growth, and dwindling resources, it offers a comprehensive framework for utilising various AI technologies to refine agricultural methods, boost productivity, and advance environmental responsibility. The concluding chapter synthesises the key insights, distils key themes, and reflects on the evolving role of AI in shaping the future of agriculture. Central to the discussion is the imperative for ethical implementation, cross-sector collaboration, and conscientious innovation to foster a just and sustainable food landscape.

Evans and Raja (2024) proposed an AI-based framework integrating AI, IoT, and cloud computing for sustainable farming. Sensors and satellite images are used for data collection. AI algorithms are used for processing the data. AI models are used for decision support for recommendations on irrigation, fertiliser application and crop rotation. Farmers can implement these AI-generated insights for resource optimisation. The authors obtained a 15% increase in yield with AI-based irrigation and a 10% yield increase in the case of ML-based yield prediction.

Climate change presents formidable challenges to agriculture, manifesting through increased weather variability, dwindling water resources, and the proliferation of novel pests and diseases. Raza et al. (2023) investigated the transformative potential of AI in reshaping agricultural analytics to support climate-resilient farming systems. AI algorithms can synthesise this data to generate actionable recommendations for planting schedules, fertiliser application, and pest management. Beyond immediate agronomic benefits, the integration of AI into climate-smart agriculture holds promise for long-term sustainability. Predictive analytics and AI-enabled supply chain optimisation can significantly improve post-harvest handling, storage, and distribution, thereby reducing food loss and strengthening overall system efficiency.

In a review, Gul and Banday (2024) examined the diverse and evolving applications of AI and ML across critical domains of agriculture. A notable advancement lies in the convergence of AI and ML with Internet of Things (IoT) technologies and autonomous agricultural machinery, which facilitates real-time monitoring and targeted interventions, boosting productivity while reducing labour demands. In the realm of crop breeding and genomics, AI accelerates the identification and development of climate-resilient crop varieties, a vital strategy for meeting rising food demands and adapting to environmental stressors. However, the widespread adoption of these technologies faces persistent challenges, including inconsistent data quality, infrastructural deficits, and high implementation costs. Disparities in access remain pronounced, particularly among smallholder farmers in low-resource settings who often lack the necessary data and technological infrastructure. Furthermore, ethical considerations-such as data privacy and the widening digital divide-must be proactively addressed to ensure inclusive and equitable deployment of AI in agriculture.

In a systematic review of 20 papers, Aijaz et al. (2025) provided a comprehensive analysis of the interdisciplinary integration of Artificial Intelligence (AI) within agriculture and food science. In the face of mounting global pressures-including climate change, population expansion, and ecological degradation- AI is positioned as a critical driver of resilience, efficiency, and sustainability across food systems. Drawing on cutting-edge research, the study examined the deployment of advanced AI methodologies- such as deep learning, reinforcement learning, and hybrid frameworks- in applications ranging from real-time crop surveillance and precision irrigation to post-harvest quality assessment and food safety monitoring. Particular attention was given to AI's role in enhancing food traceability, enabling predictive maintenance of agricultural machinery, and optimising logistics through IoT-enabled and edge computing infrastructures. The paper critically assesses how these innovations coalesce within the emerging paradigm of Agriculture and Food 6.0, promoting circular economies, lowering environmental impact, and equipping smallholder farmers with intelligent, data-informed decision-making tools. Moreover, the integration of climate resilience strategies into AI protocols is explored as a means to strengthen adaptive capacity in the face of increasingly volatile environmental conditions.

Despite its transformative potential, the integration of AI in agriculture faces several critical challenges, including data privacy concerns, high implementation costs, limited data availability, interpretability of models, technical capacity gaps, and ethical implications. Addressing these barriers is essential to ensure responsible and effective deployment. Looking ahead, AI offers vast opportunities to advance sustainable farming, strengthen climate resilience, foster interdisciplinary research, and inform evidence-based policy development. By synergising AI technologies with human expertise and collaborative frameworks, we can cultivate a future where agriculture flourishes-securing food systems and promoting sustainability for generations to come (Kumar, 2023).

Mmbando (2025) reviewed the incorporation of remote sensing and AI into climate-smart agriculture (CSA). Combining AI and remote sensing helps to regulate risks, optimise resource utilisation, and enhance agricultural practice choices. The issues like policy frameworks, capacity building, lack of knowledge among farmers, technology-phobia, high costs, ethical and privacy issues and accessibility prevent these technologies from being widely adopted. AI and remote sensing ensure food systems remain secure in changing climates.

A review by Kaya (2025) examined the pivotal role of intelligent environmental control systems, comprising sensors, automation, and AI. Case studies showed that the synergistic integration of these components can address persistent challenges such as energy efficiency, scalability, and system interoperability. Looking forward, AI-driven innovations in predictive maintenance and emerging vertical farming trends highlight the transformative potential of intelligent control systems in enhancing agricultural resilience, operational efficiency, and long-term sustainability.

After discussing various applications, benefits and challenges, Al Bakri, Al Flaiti, Al-Balushi, and Poorngalingam (2024) stressed the need to address the digital divide between large-scale commercial farms and smallholder farmers to ensure equitable access to AI technologies. Governments, policymakers, and industry stakeholders need to collaborate to develop inclusive policies and infrastructure that foster equitable AI deployment in agriculture.

The COVID-19 pandemic has amplified the vulnerabilities and systemic shortcomings of global food systems. Prevailing agricultural models often prioritise short-term productivity and profit margins at the expense of environmental stewardship and long-term sustainability. Meeting the demands of a projected global population of ten billion over the next three decades will require transformative shifts in agricultural infrastructure and automation. These challenges, however, can be addressed through the strategic deployment of smart technologies like AI across agricultural operations. AI is increasingly recognised as a catalyst for achieving global sustainability targets, particularly through its integration with renewable energy systems. Its application in agriculture is poised to rejuvenate both legacy and emerging farming landscapes by enabling the retrofitting, installation, and seamless integration of automated tools and intelligent systems (Mana, et al., 2024)

Patil (2024) noted that precision farming with AI faces many barriers. High implementation costs, data privacy concerns, and the rural digital divide limit its use. AI can empower farmers, alleviate climate threats, and secure the global food chain by encouraging innovation and inclusivity. The author emphasised the need for governmental interventions, public-private collaborations, and capacity-building to close these gaps and democratise agricultural AI technologies.

A PRISMA review of 65 papers by Waqas et al. (2025) showed that ML and DL empower the analysis of intricate datasets, fostering data-informed decision-making, minimising dependence on subjective judgment, and enhancing agricultural management practices. Although widespread adoption faces hurdles-including limited data access, challenges in model transparency, scalability issues, security risks, and user interface complexities- these obstacles can be addressed through coordinated and collaborative efforts among key stakeholders.

Using the results of some pilot studies, Arogundade and Njoku (2024) noted crop yield increases of 10 to 30%. A reduction of 15% in the overall input costs, a 15% reduction in water use, and a 20% reduction in fertiliser use with the use of AI technology. AI balances productivity with sustainability. Small farmers have limited access to data and hence a low adoption rate. Integration of AI with other technologies has an even greater potential. Digital literacy training and education on AI applications to farmers, with the support of the government and NGOs, is advocated.

Paramanik et al. (2025) discussed AI applications in crop improvement. In the case of genomics-assisted breeding, AI provides personalised, tailor-made solutions from the vast genomics datasets. ML algorithms are used to predict the desired traits from genomic markers. AI helps in plant phenotyping from the field data provided by sensors and unmanned aerial vehicles. ML algorithms process this data to map up to subtle phenotypic differences across the thousands of plots, allowing breeders to select the most desired phenotype under given environmental conditions. In the case of gene editing, ML algorithms can predict the best guide RNA sequences to minimise off-targets and maximise editing. Neural networks trained on experimental data are 90% accurate in predicting editing outcomes across different crop species. Reinforcement learning is used to optimise multiplex editing for complex traits controlled by multiple genes. These systems reduce the number of experimental iterations needed to get the desired trait combination.

According to Kumari et al. (2025), a sustainable agriculture, which combines AI-driven and conventional approaches, is necessary to meet the increasing global food demand. Ensuring equitable access and widespread adoption of advanced agricultural technologies requires coordinated action among governments, technology providers, and farming communities. A critical consideration is the alignment of technological innovations with the United Nations 2030 Agenda for Sustainable Development. Precision agriculture, powered by artificial intelligence (AI), the Internet of Things (IoT), and machine learning (ML), directly contributes to SDG 2 (Zero Hunger) by enhancing productivity and strengthening food security. Moreover, these technologies promote sustainable agricultural practices by optimising resource utilisation, minimising environmental impact, and improving land stewardship. In doing so, they support broader sustainability objectives, including SDG 12 (Responsible Consumption and Production), SDG 13 (Climate Action), and SDG 15 (Life on Land).

Discussion

Use of AI transforms arid practices into agile practices. Agribusiness involves crop production, post-harvest processing and marketing. Most papers addressed the crop production aspect. Some specific exceptions were crop improvement (Paramanik et al., 2025), levels of yield increase and decrease in input utilisation from pilot studies (Arogundade & Njoku, 2024), climate change (Aijaz et al., 2025; (Gul & Banday, 2024; Raza et al., 2023; Zidan & Febriyanti, 2024; Nirnjan et al., 2025), land models (Dagon et al., 2020), pest attacks (Holuša & Kaláb, 2023), grain supply chain (Zhang & Zhou, 2025) and agility (Sudha et al., 2025; Dey et al., 2025).

The reviewed articles generally discussed various AI applications, how they are used, the benefits and challenges. At the local level, sustainable agriculture is important. At the global level, food security for the growing population is important (Mana et al., 2024; Mmbando, 2025; Lal & Mishra, 2025; WEF, 2025). Integration of AI with other technologies leads to synergistic effects of the component technologies. Smallholders are unable to access AI technology due to their resource constraints, and this leads to a digital divide. Deliberate policy and strategic interventions from the governments are required to address these problems (Patil, 2024; al Bakri et al., 2024). Kumari et al. (2025) linked precision farming using AI, IoT and ML technologies to specific SDG goals of the UN targeted for 2030. AI technologies with human expertise (Kumar, 2023) and with traditional methods.

CONCLUSIONS

Considering that AI applications transform the current agricultural production systems into agile production systems, this review provided much information on how various AI and other technologies contribute to such a transformation. Production is the first stage of agribusiness. At the local level, AI applications transform agriculture into sustainable food production. At the global level, it is concerned with global food availability and security.

Apart from production, AI addresses product supply chains, post-harvest processing and marketing through market intelligence, to predict price and volume of arrivals in markets. AI chatbots recommend actions for agribusiness based on these predictions. All these apply to farmers who market their products themselves and large agribusiness firms. However, unless governments intervene with appropriate policies and strategies, a digital divide between the two will limit the access of AI technologies by small farmers.

There are many limitations to this review. Using only Google Scholar, restricting to 2020-2025, English language, and some exclusion criteria might have prevented the selection of many important papers.

Some recommendations are listed below:

1. To ensure wider adoption and practice of AI in agriculture and agribusiness, governments should devise policies and strategies to remove the digital divide between small farmers and large agribusiness firms.
2. Stakeholders should collaborate to ensure full and proper utilisation of AI in agriculture to its full potential. All barriers to this need to be addressed by competent authorities.
3. There should be more research on the removal of barriers and addressing the challenges to AI adoption by all those engaged in agriculture and agribusiness.

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