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Review Paper

Artificial intelligence in agriculture: A review of recent advances, challenges, and opportunities

Tayyeb Nazghelichi[1*], Mohammadhadi Ghafari[2], Abolfazl Aghajanlou[3]

[1] *Department of Biosystems Engineering, Gorgan University of Agricultural Sciences and Natural Resources, Gorgan, Iran*
[2] *University of Urmia, Urmia, Iran*
[3] *Department of Technology and Agriculture, Faculty of Aburaihan, University of Tehran, Tehran, Iran*

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*** Corresponding author**
nazghelichi@gau.ac.ir

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ABSTRACT

Global agriculture faces profound challenges, including resource scarcity, climate change, and a 70% increase in food demand by 2050, resulting in 20-40% annual crop losses. Artificial intelligence (AI) is a key transformative force, integrating machine learning (ML), deep learning (DL), and the Internet of Things (IoT) to deliver data-driven solutions for precision agriculture, enhancing productivity, sustainability, and resilience. This systematic review, based on a comprehensive search in databases like Web of Science, Scopus, and Google Scholar focusing on peer-reviewed English-language articles, analyzes AI applications in crop yield prediction (with over 96% accuracy via satellite imagery), pest and disease detection (using CNNs), soil and environmental monitoring (with IoT sensors), market price forecasting (with LSTM), and smart mechanization (such as autonomous tractors). In Iran, AI shows promise in managing strategic crops (such as wheat using RF and SVM), soil assessment (erosion mapping), and livestock (disease prediction), though challenges like data scarcity, weak infrastructure, and socioeconomic barriers hinder its expansion. Research gaps include insufficient integration with post-harvest management, a lack of longitudinal studies, and the absence of ethical standards. This paper, by proposing future paths such as interdisciplinary collaboration and supportive policies, emphasizes AI's potential for achieving sustainable agriculture and food security, boosting national food security by up to 20%, positioning Iran as a regional leader in the next generation of AgriTech.

1. Introduction

Agriculture faces significant statistical challenges in efficiently using scarce resources, coping with the complex effects of climate change, and meeting a growing global population's needs. Estimates suggest that by 2050, global food demand will rise by almost 70% as cultivable land becomes scarce due to urban expansion and soil degradation (Valin et al., 2014). Unpredictable weather patterns and pests intensify these challenges, accounting for 20% to 40% of global crop damage annually. This underscores the need for innovative, data-driven strategies to improve agricultural resilience and productivity (FAO, 2021; Savary et al., 2019). Given these challenges, it is crucial to identify how AI can bridge problems to solutions. By integrating advanced technology into agriculture, AI directly addresses these issues by enhancing resilience and productivity through data-driven solutions. This paradigm shift extends to smart agriculture, where IoT leverages artificial intelligence (AI) and big data analytics. This integration enhances global effectiveness while minimizing ecological impacts and optimizing resource use. IoT-based systems provide current soil moisture levels, pH, and nutrient breakdown (Talaviya et al., 2020). Such systems enable precise scheduling of irrigation and fertilization, which is vital for sustainability.

Additionally, agricultural decision-making relies heavily on forecasting, which empowers farmers with predictive analytics to choose the most suitable crops, manage irrigation, and control pests. Seasonal climate forecasting reduces the risks of extreme weather events, such as droughts or heavy rainfall, stabilizes yields, and minimizes economic losses. Estimates of forecasting effectiveness are often constrained by long-standing issues, including data quality and the successful delivery of probabilistic forecasts to end users (Joseph et al., 2025). By addressing these limitations, we can fully realize the potential of agriculture-based forecasting. AI has emerged as a transformative force in modern agriculture, offering sophisticated solutions for predictive analytics, resource optimization, and automated decision-making. Leveraging machine learning (ML), AI-driven technologies are increasingly deployed for applications such as crop health monitoring, pest detection, and yield prediction.

A notable example is the use of AI algorithms to analyze satellite imagery, enabling the early detection of crop stress and facilitating timely interventions (Shaikh et al., 2022). These advancements underscore AI's capacity to revolutionize agricultural practices, paving the way for more efficient, sustainable, and resilient farming systems. Figure 1 presents a conceptual diagram that delineates the interplay between the statistical challenges facing agriculture and the innovative solutions enabled by AI and smart technologies, highlighting their transformative potential in this domain.

2. Review Methodology and Scope

This examination focuses on how AI can help agriculture address the complex problems farmers face today. It aims to investigate the current state of AI in agriculture, identify key

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technological breakthroughs, and propose potential research paths to improve farming productivity, efficiency, and sustainability. To achieve this goal, a comprehensive literature review was conducted across scholarly databases, including Web of Science, Scopus, and Google Scholar. The study incorporated a blend of terms such as *artificial intelligence*, *machine learning*, *deep learning*, *precision agriculture*, *precision farming*, *crop monitoring*, *yield monitoring*, *yield prediction*, and *pest detection*. The review included only peer-reviewed journal articles, conference papers, and book chapters. Research was filtered for relevance to AI in agricultural applications, methodological rigor, and the practical value of its findings. The selected works were classified by the type of AI technology used (ML, computer vision, deep learning) and by the opportunities and challenges identified in each domain. This systematic classification enabled an in-depth analysis of dominant trends, technical approaches, and outcomes across various agricultural settings. Nevertheless, the review's limitation is possible selection bias due to its sole consideration of English-language articles and research indexed in the databases cited.

3. Overview of AI Methodologies

AI comprises computational methods that learn from data, improve over time, and enable more intelligent decision-making. In agriculture, the most commonly used techniques include ML, deep learning, artificial neural networks (ANNs), decision trees, support vector machines (SVMs), and ensemble learning methods. ML algorithms are widely applied to structured datasets for regression, classification, and clustering. Decision-tree-based models, such as random forests and gradient boosting machines, are preferred for their high predictive power and ease of interpretation (Liakos et al., 2018a). Additionally, SVMs have demonstrated remarkable success in binary classification tasks, such as identifying crop diseases and soil types (Talaviya et al., 2020).

Deep learning, a powerful sub-discipline of ML, uses multi-layered neural architectures to identify complex patterns in data. CNNs are highly effective at analyzing image data and have been used to detect plant diseases, identify weeds, and track growth stages with precision (Kamilaris & Prenafeta-Boldú, 2018; Zhang et al., 2017). Temporal sequence modeling has employed recurrent neural networks (RNNs), particularly long short-term memory (LSTM) networks, in applications such as weather and commodity price prediction (Zhang & Tang, 2024). Additionally, the hybrid multi-learning AI paradigm is becoming more prevalent. The ability of CNN-LSTM models to encode both spatial and temporal dependencies is a significant improvement for crop monitoring systems (P. Chen et al., 2023).

4. Applications of Artificial Intelligence in the Agricultural Industry

Over the last decade, AI has emerged as a game-changing tool in the agricultural sector, offering advanced, data-driven solutions to persistent issues such as crop rotation patterns and pest outbreaks. The utilization of AI in precision agriculture has significantly boosted productivity and resource efficiency and promoted environmentally friendly farming practices.

4.1. Crop yield prediction

Food security, supply chain optimization, and policy development rely heavily on yield prediction. AI models that integrate satellite imagery, climatic data, and historical agricultural data have been shown to accurately predict yields. By training deep learning models on multispectral remote sensing data, researchers have accurately estimated yields of major crops such as wheat and maize (Jabed & Azmi Murad, 2024). With 96% accuracy, these models can alert farmers two weeks earlier than conventional estimates, enabling timely management actions such as adjusting irrigation schedules, optimizing fertilization plans, and preparing logistics for harvest. This advanced notice allows farmers to make informed decisions, potentially increasing yields and reducing losses.

4.2. Pest and disease detection

Preventing the spread of crop diseases and pest infestations can significantly reduce agricultural losses and pesticide use. CNNs trained on annotated field images have been shown to reliably detect symptoms of common diseases such as blight, rust, and powdery mildew, surpassing traditional diagnostic techniques (Simhadri et al., 2025). Also, real-time pest diagnosis can be achieved through AI-powered pest classification systems that use aerial or smartphone images (Pierre Nyakuri et al., 2024; Silva et al., 2024).

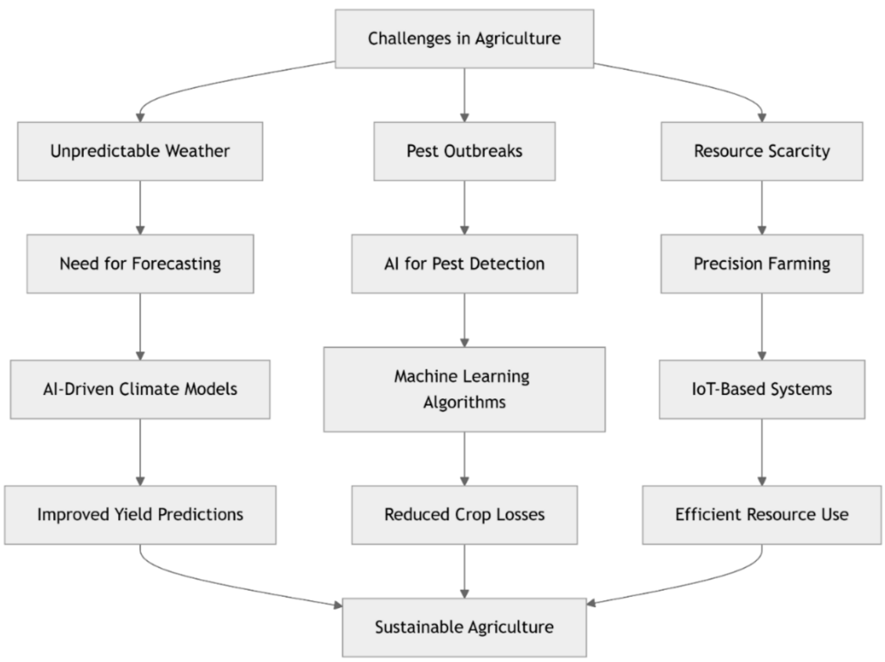

Figure 1. Challenges and solutions to agricultural challenges through artificial intelligence

4.3. Environmental and soil monitoring

Environmental and soil monitoring via IoT and wireless sensor networks enables dynamic observation of variables such as soil moisture, temperature, and humidity. These systems enable predictive analytics for precision irrigation and nutrient management, facilitating more efficient water use and directly contributing to improved water-use efficiency as a key sustainability metric (Guebsi et al., 2024). Furthermore, high-resolution field data is captured by drone-mounted multispectral cameras and processed using ML algorithms to identify water stress, nutrient deficiencies, and plant activity, thereby reducing the carbon footprint by optimizing resource allocation and minimizing unnecessary inputs (Matese et al., 2024).

4.4 Market intelligence and price forecasting

Fluctuations in commodity prices directly impact farm profitability. Advanced AI-based time series models, particularly LSTM and Gated Recurrent Units (GRU), can effectively model complex temporal dependencies, offering more accurate and timely market forecasts than traditional statistical methods such as ARIMA (Kouakan Adanin & Balungu, 2025; Manogna, Dharmaji, and Sarang, 2025; Paul et al., 2025). Figure 2 shows the projected market size for AI in agriculture.

5. The Role of Mechanization in the Transformation of Modern Agriculture

Agricultural mechanization is known as the engine driving productivity in the agricultural sector. With modern machinery, traditional processes such as planting, tending, harvesting, and product processing are carried out faster, more accurately, and more efficiently (Akter et al., 2024). Especially in conditions of water resource crisis, human resource shortages, and climate change, increasing mechanization is not only a choice but also a necessity (Balai et al., 2025). In recent years, technologies such as AI, Internet of Things (IoT), renewable energy, and remote control systems have given a new dimension to agricultural mechanization. The introduction of self-driving tractors, pesticide-spraying drones, harvesting robots, and intelligent resource management systems represents significant advancements in this field (Mim et al., 2025). These intelligent devices reduce the need for human intervention while enabling uninterrupted operation, greater precision, and real-time condition analysis (Shamshiri et al., 2018).

Furthermore, AI is crucial for evaluating plant and animal health, allowing for early detection of diseases and pests from field or animal images, which facilitates more effective prevention measures (Younas et al., 2025). As agricultural mechanization evolves, emerging technologies have significantly transformed the design, deployment, and maintenance of machinery. To expedite the adoption of autonomous tractors in smallholder settings, a structured pathway can be followed: initial implementation in pilot plots to refine technology in realistic conditions; development of cooperative sharing models where farmers can access tractors collectively, reducing individual financial burden; and finally, scaling up with government and private sector support to broaden reach and impact. Table 1 illustrates the most prominent innovations, such as AI, the IoT, renewable energy integration, and robotics. These technologies have proven to improve efficiency, reduce labor dependency, and lower operational costs across diverse agricultural contexts (Sami et al., 2025; Hajian et al.,2025; Kaur, Nehra, and Bhushanwar, 2025).

In developing nations, the process of mechanization faces several obstacles, including infrastructure deficiencies and social unrest. Table 2 summarizes the most pressing problems. Three primary sectors can be utilized to achieve a sustainable and widespread mechanization:

- Infrastructure development and access. Important steps include the establishment of appropriate rural roads, dependable electricity supply through repair stations, machinery repair centers, and solar energy stations (Balai et al, 2025).
- Shared and subsidized models. Shared machinery models, such as the "Uber for agricultural machinery," are being implemented in densely populated nations. In this model, ownership costs are significantly reduced as farmers rent machines (Akter, 2024).

Table 1. Technologies in AI and their application in agriculture

Technology	Main Application in Agriculture	Key Benefits & Outcomes	References
Artificial Intelligence (AI)	Intelligent machine control, equipment failure prediction, data analysis for farming decisions	Error reduction, increased productivity & yield optimization	Akter (2024); Younas et al. (2025)
Internet of Things (IoT)	Connecting sensors to machinery and farm equipment	Real-time monitoring, precise and timely decision-making	Kaur et al. (2025)
Renewable Energy	Powering light machinery & equipment with solar panels and clean sources	Reduced fuel consumption, environmental sustainability, lower energy costs	Hajian et al. (2025); Sami et al. (2025)

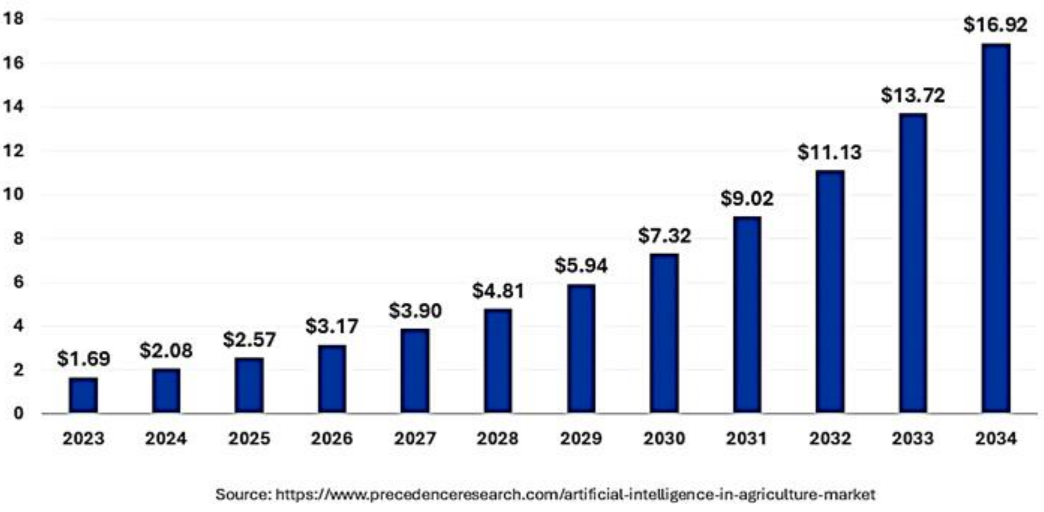

Figure 2. AI in agriculture market size 2023 to 2034 (million USD)

- Education and awareness. It is essential to establish technical training centers in rural areas and provide training courses for agricultural machinery maintenance to improve the skills of maintenance and operators. These trainings will help agricultural service providers to become competitive and provide better services. In many rural areas, technical knowledge and regular training are recognized as major obstacles to agricultural mechanization (L. Chen et al., 2023). In addition, agricultural machinery service organizations are responsible for providing technical training and safety training. To meet modern training needs, virtual reality-like technologies are being developed for complex agricultural machinery maintenance training (Akinfiresoye & Agbetoye, 2013).

6. Advances and Empirical Evidence in Agriculture

Empirical research on the use of AI in agriculture has grown over the past two years. This body of research highlights the integration of transformer architectures, federated learning, and reinforcement learning, with applications specific to high-tech and resource-limited settings, while also acknowledging geographic and contextual diversity. According to a comparative analysis of high-impact studies published in 2024 and 2025, there has been a reversal in both model sophistication and domain specificity. To advance this field, emerging scholars should prioritize addressing the lack of integration between existing AI models and post-harvest management applications, as well as ethical and regulatory challenges. Providing clear direction on these key issues can significantly enhance the effectiveness and applicability of AI technologies in agriculture.

AI has become a revolutionary force in agriculture, enabling precision, automation, and sustainability across many fields. Precision agriculture has embraced AI, with recent surveys highlighting the use of ML, computer vision, and IoT for crop management, disease detection, and resource optimization (Hossen et al., 2023). Additionally, a study explored how AI can enhance agricultural decision-making by utilizing real-time data collection and analysis for pest management and crop monitoring (Liakos et al., 2018b), among other things. However, another study on disruptive AI in agriculture examined the potential of these technologies to enhance agricultural production, pest control, and soil quality monitoring, while also considering the ethical issues and environmental consequences of their use (Hemming et al., 2019).

Table 2. Challenges and Barriers to Adopting Smart Agriculture / Precision Farming Technologies

Category	Main Challenges / Barriers	Key References
Economic	High costs of purchasing advanced machinery, equipment, and spare parts	Akter (2024)
Infrastructure	Lack of suitable roads, limited access to service workshops, and insufficient fuel stations	Balai et al. (2025)
Social and Cultural	Resistance to new technologies among traditional farmers, and fear of job losses due to automation	Akintuyi, (2024); Patel, (2023)
Educational	Limited technical knowledge and skills for repair, maintenance, and optimal use of smart machines and systems	Mim et al. (2025); Kaur et al. (2025)
Political and Legal	Absence of supportive government policies, high import tariffs, and taxes on advanced agricultural machinery	Younas et al. (2025)

Furthermore, a comprehensive analysis evaluated AI's contributions to food safety and security through outbreak detection, risk prediction, and food supply chain optimization, including applications in sustainable food systems, such as alternative protein production. Real-time monitoring of environmental parameters, such as soil moisture and temperature, even in areas with inadequate network connectivity, has been the focus of research integrating AI and IoT for irrigation and pest control (Hemming et al., 2019).

An integrated analysis of AI in agriculture categorized it into different areas related to soil, crop, and livestock management, highlighting advancements in methods such as weed detection, disease diagnosis (Wang et al., 2025), or yield prediction, with important implications for increased productivity and sustainability. A systematic review examined AI's ability to address climate change and pest infestations, affirming its role as the primary driver of sustainable farming (Kaur et al., 2025). Moreover, the use of AI in tools such as innovative irrigation systems, automated fertilizer application systems, and self-driving farming machinery has demonstrated greater effectiveness and accuracy than conventional methods (Talaviya et al., 2020). A research study used convolutional neural networks (CNNs) to explore onion crop patterns, achieving classification accuracies of 90%-99.92%, highlighting the potential of AI to improve irrigation methods and promote healthy crops (López-Martínez et al., 2024). Table 3 lists a summary of key studies on AI applications in agriculture.

7. AI in Agricultural Mechanization in Iran: Opportunities and Challenges

According to recent studies, AI brings both significant challenges and promising opportunities to the mechanization and modernization of agriculture in Iran. The country is recognized as one of the leading nations in AI research applied to agriculture (Ruiz-Real et al., 2020).

7.1. Opportunities

Given the growing challenges of water scarcity, climate change, and declining soil productivity, Iran faces unprecedented opportunities to transform traditional agriculture into an advanced and sustainable system (Emami et al., 2018). AI and digital technologies can play a vital role in this transformation. One of the most important opportunities is to improve water resource management through precision and smart irrigation systems (Lakhiar et al., 2024). Using IoT sensors and ML algorithms, these systems can reduce water consumption by up to 30 percent while maintaining crop productivity. Powering smart irrigation systems with renewable energy, especially solar energy, is well suited to Iran's climatic conditions, thereby increasing productivity and reducing energy costs (Daraz et al., 2025). On the other hand, developing rain-fed agriculture with new and more effective strategies can be highly effective in Iran's mountainous and semi-arid regions (Firoozzare et al., 2023).

Table 3. Summary of key studies on AI applications in agriculture

Study	Field	Method	Aim
Nimmala et al. (2024)	Precision farming	ML, CV, IoT	Crop/disease/resource optimization
Sinha et al. (2025)	Disruptive technologies & ethics	AI, ML	Productivity, pest/soil monitoring, and ethical concerns
Rugji et al. (2024)	Food safety and security	Predictive AI	Early warnings, risk analysis, and sustainable food systems
Indira et al. (2023)	IoT-based monitoring	AI, IoT	Irrigation optimization, low-network applicability
López-Martínez et al. (2024)	Deep learning in crop management	CNN	Up to 99.92% accuracy in crop pattern classification

Agricultural mechanization is another opportunity to boost productivity and reduce labor costs. Intelligent, automated machines, especially in transplanting, planting, irrigation, and harvesting, can reduce manual labor and improve work quality. AI algorithms can diagnose plant diseases, determine the precise nutritional needs of crops, and predict yields based on climatic conditions and soil characteristics. These capabilities help Iranian farmers make data-driven decisions and optimize resources. However, implementing these technologies requires a comprehensive approach that includes appropriate training, the development of digital and information technology infrastructure, and supportive government policies (Becerra et al., 2023). Small and medium-sized farmers in Iran are particularly in need of applied training programs and joint technology use, since individual investment is not feasible for each farmer. AI-based recommender systems and mobile and web-based applications can provide practical guidance for improving farming practices without the need for complex hardware. Developing communication infrastructure and the IoT in rural areas, engaging the private sector and NGOs, and pursuing inclusive policymaking that protects farmers' rights and interests are the foundations for the successful implementation of these technologies in Iran. By following this path and drawing on the successful experiences of other developing countries, Iran can achieve digital transformation in its agriculture and ensure the country's food security.

7.2 Challenges

Despite its great potential, agricultural mechanization in Iran faces several obstacles that hinder the widespread adoption of AI technologies. Economic and Managerial Challenges: Major obstacles include farmers' limited financial capacity and the inefficiency of subsidy programs for purchasing machinery (Behpouri et al., 2023). The absence of a clear, practical strategy for mechanization development is also a persistent problem. Additionally, a shortage of specialized management remains a barrier (Hormozi et al., 2012). Technical and Infrastructural Challenges: A large number of outdated machines and incomplete tractor equipment represent major technical issues (Bagheri and Moazzen, 2009). Unequal distribution of mechanization across regions also restricts the expansion of AI-based technologies (Zha, 2020).

Educational and Extension Challenges: The slow adoption of modern technologies by farmers and the inefficiency of agricultural education and extension programs are other significant limitations (Bagheri & Moazzen, 2009). Developing mechanization requires government support for research and development, hiring young graduates, and strengthening educational programs (Omid et al., 2008). Crop-Specific Limitations: In some instances, biological characteristics of crops, such as the low height of saffron plants, limit mechanization more than economic or social factors (Hayati & Marzban, 2025). To overcome these challenges, researchers suggest enhancing producers' and machinery operators' technical skills, strengthening agricultural organizations, and improving financial mechanisms (Bagheri & Moazzen, 2009).

8. Research Gaps in AI-driven Agriculture

Despite rapid advancements, several critical gaps continue to limit the full realization of AI's transformative potential in agriculture. While AI has proven effective for crop monitoring and irrigation, its integration with nutrient management and intelligent sensing remains limited. The intersection of these areas is essential for the development of sustainable agricultural systems (Bannerjee et al., 2023). Besides, AI and IoT adoption are hindered by high infrastructure costs, non-interoperability, and unreliable connectivity, especially in rural and developing regions. This is hindering inclusive access to intelligent farming technologies (Guebsi et al., 2024).

Precision agriculture research is currently dominated by crop research, whereas AI-based livestock monitoring applications are underdeveloped. A balance must be redressed to permit comprehensive agricultural development (Hemming et al., 2019b). Perhaps the greatest challenge is the lack of high-quality, domain-specific data, particularly for specialty crops and growth-stage classification, which undermines AI model training and performance (Benos et al., 2021).

As another research gap, data privacy, algorithmic transparency, and accountability are poorly researched. More importantly, there is insufficient standardized international regulation for AI deployment in agriculture (Kaur et al., 2025). Infrastructural inequalities, limited digital skills, and cultural resistance to automation widen the digital divide, especially among marginalized farming communities (Talaviya et al., 2020). AI research has not yet emphasized post-harvest areas such as cold chain optimization and food quality monitoring, although these are significant for reducing food loss (Fadiji et al., 2023). The lack of cross-disciplinary collaboration, especially among robotics, ML, and environmental sciences, hinders the development of comprehensive AI systems for agriculture (Matese et al., 2024). Variety in AI models and evaluation processes hinders comparability. Having benchmark standards is essential to ensure standard, transparent, and scalable deployments of AI (Kalokyri et al., 2025)

9. Application of AI in the Agriculture of Iran

Agriculture remains a cornerstone of Iran's economy, contributing significantly to food security, employment, and rural development. However, the sector faces mounting pressures from water scarcity, climate variability, soil degradation, and the need for higher productivity to support a growing population. AI, including ML and deep learning techniques, is emerging as a powerful tool to address these challenges in Iran. Recent research demonstrates the active and promising applications of AI across crop management, soil assessment, livestock production, and precision farming, although most efforts remain in the research and model development phase rather than in widespread on-farm deployment.

9.1 AI in crop management and yield prediction

In Iran, ML models are increasingly used to improve crop mapping, yield estimation, and resource optimization, particularly for strategic crops such as wheat, barley, and maize. These approaches leverage satellite imagery (e.g., Landsat-8, Sentinel-2) and time-series data to enable accurate monitoring and decision-making. A key advancement is the development of machine-learning-driven crop-mapping frameworks that use Landsat-8 time series and classical algorithms, including Decision Tree (DT), Random Forest (RF), Rotation Forest (RoF), Support Vector Machine (SVM), and Dynamic Time Warping (DTW). As illustrated in Figure 3, these methods have achieved high accuracy (approximately 96%) in crop classification, supporting sustainable agriculture by enabling the estimation of cultivated areas and annual yields of strategic crops (Khosravi, 2025).

9.2 AI in soil management and environmental monitoring

AI plays a vital role in soil-related assessments, which are crucial for Iran's arid and semi-arid regions. Applications include digital mapping of soil properties and downscaling satellite data for precise environmental monitoring. Notable examples include digital mapping of the soil erodibility factor in northwestern Iran using ML models, generating risk maps to guide land management and erosion control (Khosravi Aqdam et al., 2022), as well as advanced spatiotemporal downscaling of MODIS land surface temperature data in Qazvin Province, combining Sentinel-1 and Sentinel-2 imagery with Random Forest regression on Google Earth Engine. This approach produces high-resolution (10 m) daily LST maps, improving monitoring of agricultural landscapes, irrigation needs, and crop stress (Faraji et al., 2025). Figure 4 demonstrates a conceptual workflow of the spatiotemporal downscaling process applied in Qazvin Province, illustrating how multi-source satellite data are integrated with Random Forest regression to generate high-resolution Land Surface Temperature (LST) maps.

9.3 AI in livestock production systems

The livestock sector in Iran is beginning to benefit from AI for animal health monitoring, feed optimization, and disease management, though progress is primarily in model development rather than large-scale implementation. Research employs data-driven modeling, computer vision, IoT, and ML to classify chewing and rumination in dairy cows from sound signals, predict calving difficulty in Holstein cows using neural networks, forecast brucellosis incidence, estimate body weight from images, and model energy ratios in broiler production (Ghavipanje et al., 2025). These applications aim to improve animal welfare, reduce losses, and enhance productivity across dairy, poultry, and other systems. However, most studies remain theoretical, with limited on-farm deployment due to systemic barriers (Ghavipanje et al., 2025).

9.4 Challenges and barriers to adoption

Despite promising research, widespread AI adoption in Iranian agriculture is hindered by interconnected challenges:

- Data scarcity: Insufficient high-quality, large-scale datasets for training and validating robust models.
- Economic and infrastructural limitations: High costs, inadequate on-farm infrastructure (e.g., IoT connectivity), and questions of feasibility for smallholder farmers.
- Regulatory and ethical gaps: Lack of clear frameworks for data ownership, privacy, and ethical use, plus inconsistencies in reported methods that complicate validation.
- Transition from research to practice: Most efforts focus on model development without practical integration (Ghavipanje et al., 2025).

To unlock AI's full potential, Iran needs multi-disciplinary collaboration among veterinarians, computer scientists, agronomists, engineers, and policymakers. A timeline with specific milestones can serve as a catalyst for these collaborative efforts, such as establishing a national shared dataset by 2027 to drive data consistency and accessibility. Key recommendations include: Building national datasets and improving precision farming infrastructure. Developing localized, affordable AI solutions tailored to Iran's agro-ecological diversity. Establishing regulatory guidelines and ethical standards. Fostering partnerships for field deployment, validation, and scaling. These steps, anchored in a clear timeline, will pave the way for AI to drive sustainable intensification, boost the circular economy, and position Iran as a regional leader in smart agriculture.

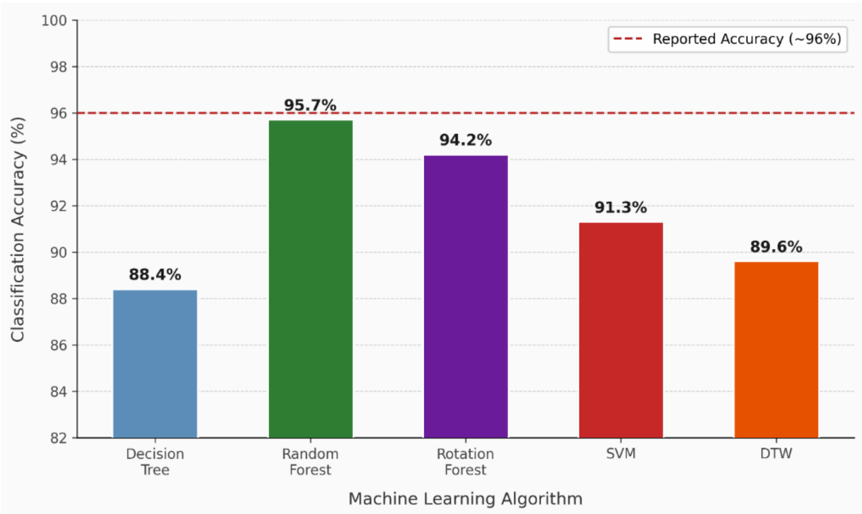

Figure 3. Crop classification accuracy of ML algorithms using Landsat-8 time series data in Iran

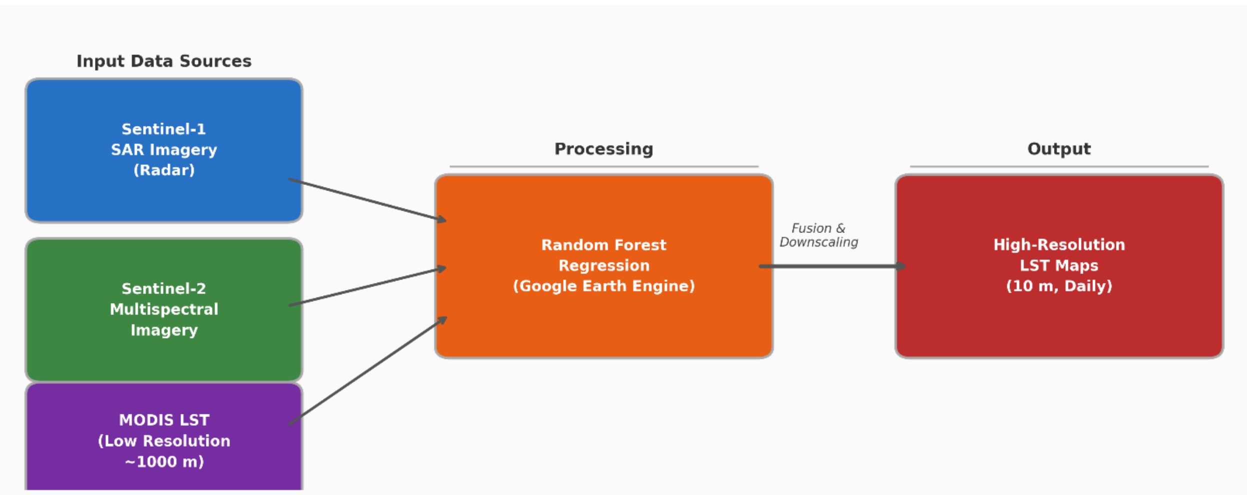

Figure 4. Workflow of Spatiotemporal LST Downscaling Using 'Multi-Source Satellite Data and Random Forest in Qazvin Province, Iran

10. Conclusion

Finally, this review article highlights the transformative role of AI in modern agriculture, demonstrating how advanced technologies such as ML, deep learning, and the IoT can address statistical, climate, and resource challenges. By examining key applications of AI in crop yield prediction, pest and disease detection, soil and environmental monitoring, and market forecasting, it is clear that these technologies increase productivity and lead to more sustainable and efficient agriculture. Empirical evidence from recent studies (2024-2025) confirms that integrating AI with mechanization, especially in countries such as Iran, offers opportunities for economic modeling, precise resource management, and attracting younger generations to the agricultural sector, while challenges such as infrastructural, economic, and educational constraints remain significant obstacles.

Identified research gaps, including a lack of high-quality data, ethical issues, and insufficient focus on post-harvest and livestock applications, underscore the need for further research and interdisciplinary collaboration. To overcome these barriers, policymakers should prioritize developing infrastructure, collaborative and educational models, and regulatory support to enable sustainable mechanization in developing countries. Ultimately, AI is key to global food security and a powerful tool for combating climate change and promoting socio-economic sustainability. With smart investments in this area, the future of agriculture will be brighter and more resilient.

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Competing interests

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Data availability statement

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References

Akinfiresoye, W. A., & Agbetoye, L. A. S. (2013). Evaluation of farm machinery usage and maintenance in Ondo state, Nigeria. *International Journal of AgriScience*, *3*, 807-813.

Akter, J., Nilima, S. I., Hasan, R., Tiwari, A., Ullah, M. W., & Kamruzzaman, M. (2024). Artificial intelligence on the agro-industry in the United States of America. *AIMS Agriculture & Food*, *9*(4), 959-979. https://doi.org/10.3934/agrfood2024052

Bagheri, N., & Moazzen, S. A. (2009). Optimum strategy for agricultural mechanization development in Iran. *Journal of Agricultural Technology*, *6*(1), 225-237.

Balai, P. S., Sheikh, A., Rabha, G., Das, S., Kuli, B. K., & Raj, M. (2025). Revolutionizing agricultural machinery: The role of AI, IoT, and renewable energy in enhancing efficiency and sustainability. *International Journal of Scientific Research in Science and Technology*, *12*(2), 813-830. https://doi.org/10.32628/IJSRST251222626

Behpouri, A., Farokhzadeh, S., Zinati, Z., & Khosravi, Z. (2023). Use of multivariate analysis and machine learning methods to characterize traits contributing to wheat yield diversity. *Spanish journal of agricultural research*, *21*(1), 901. https://doi.org/10.5424/sjar/2023211-19835

Benos, L., Tagarakis, A. C., Dolias, G., Berruto, R., Kateris, D., & Bochtis, D. (2021). Machine learning in agriculture: A comprehensive updated review. *Sensors*, *21*(11), 3758. https://doi.org/10.3390/s21113758

Chen, L., Zhang, Z., Li, H., & Zhang, X. (2023). Maintenance skill training gives agricultural socialized service providers more advantages. *Agriculture*, *13*(1), 135. https://doi.org/10.3390/agriculture13010135

Chen, P., Li, Y., Liu, X., Tian, Y., Zhu, Y., Cao, W., & Cao, Q. (2023). Improving yield prediction based on spatio-temporal deep learning approaches for winter wheat: A case study in Jiangsu Province, China. *Computers and Electronics in Agriculture*, *213*, 108201. https://doi.org/10.1016/j.compag.2023.108201

Daraz, U., Bojnec, T., & Khan, Y. (2025). Energy-efficient smart irrigation technologies: A pathway to water and energy sustainability in agriculture. *Agriculture*, *15*(5), 554. https://doi.org/10.3390/agriculture15050554

Emami, M. H., Almassi, M., Bakhoda, H., & Kalantari, I. (2018). Agricultural mechanization, a key to food security in developing countries: Strategy formulating for Iran. *Agriculture & Food Security*, *7*, 24. https://doi.org/10.1186/s40066-018-0176-2

Fadiji, T., Bokaba, T., Fawole, O. A., & Twinomurinzi, H. (2023). Artificial intelligence in postharvest agriculture: Mapping a research agenda. *Frontiers in Sustainable Food Systems*, *7*, 1226583. https://doi.org/10.3389/fsufs.2023.1226583

Faraji, Z., Kaviani, A., & Khosravi, L. (2025). Advanced spatiotemporal downscaling of MODIS land surface temperature: Utilizing Sentinel-1 and Sentinel-2 data with machine learning technique in Qazvin Province, Iran. Environmental Monitoring and Assessment, 197, 943. https://doi.org/10.1007/s10661-025-14411-w

Firoozzare, A., Saghaian, S., Bahraseman, S. E., & Dehghani Dashtabi, M. (2023). Identifying the best strategies for improving and developing sustainable rain-fed agriculture: An integrated SWOT-BWM-WASPAS approach. *Agriculture*, *13*(6), 1215. https://doi.org/10.3390/agriculture13061215

Food and Agriculture Organization of the United Nations. (2021). *World food and agriculture – Statistical yearbook 2021*. FAO. https://www.fao.org

Ghavipanje, N., Fathi Nasri, M. H., & Vargas-Bello-Pérez, E. (2025). Trends and future directions of artificial intelligence applications in Iranian livestock production systems: A review. *Annals of Animal Science*, *25*(3), 865–874. https://doi.org/10.2478/aoas-2024-0098

Hajian, M., Sami, S., & Nazghelichi, T. (2025). Deep learning framework for joint prediction of energy resources in an industrial building. *Biomechanism and Bioenergy Research*, *4*(4), 95–109. https://doi.org/10.22103/bbr.2025.25960.1134

Hayati, A., & Marzban, A. (2025). A review of the ergonomic problems of agricultural activities in connection with mechanization: Some Iranian farm works as instances. *Work*, *82*(3), 715–726. https://doi.org/10.1177/10519815251351602

Hemming, S., Zwart, F., Elings, A., Righini, I., & Petropoulou, A. S. (2019). Remote control of greenhouse vegetable production with artificial intelligence—Greenhouse climate, irrigation, and crop production. *Sensors*, *19*(8), 1807. https://doi.org/10.3390/s19081807

Hormozi, M. A., Asoodar, M. A., & Abdeshahi, A. (2012). Impact of mechanization on technical efficiency: A case study of rice farmers in Iran. *Procedia Economics and Finance*, *1*, 176–185. https://doi.org/10.1016/S2212-5671(12)00021-4

Hossen, M. I., Fahad, N., Sarkar, M. R., & Rabbi, M. R. (2023). Artificial intelligence in agriculture: A systematic literature review. *Turkish Journal of Computer and Mathematics Education*, *14*(1), 137–146. https://doi.org/10.17762/turcomat.v14i1.13384

Jabed, M. A., & Murad, M. A. A. (2024). Crop yield prediction in agriculture: A comprehensive review of machine learning and deep learning approaches, with insights for future research and sustainability. *Heliyon*, *10*(24), e40836. https://doi.org/10.1016/j.heliyon.2024.e40836

Joseph, J. E., Rao, K. P. C., Swai, E., Whitbread, A. M., & Rötter, R. P. (2025). How beneficial are seasonal climate forecasts for climate risk management? An appraisal for crop production in Tanzania. *Climate Risk Management*, *47*, 100686. https://doi.org/10.1016/j.crm.2024.100686

Kalokyri, V., Tachos, N. S., Kalantzopoulos, C. N., Sfakianakis, S., Kondylakis, H., Zaridis, D. I., Colantonio, S., Regge, D., Papanikolaou, N., Marias, K., Fotiadis, D. I., & Tsiknakis, M. (2025). AI model passport: Data and system traceability framework for transparent AI in health. *Computational and Structural Biotechnology Journal*, *28*, 386–404. https://doi.org/10.1016/j.csbj.2025.09.041

Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, *147*, 70–90. https://doi.org/10.1016/j.compag.2018.02.016

Kaur, R., Nehra, D., & Bhushanwar, K. (2025). Enhancing sustainability, climate resilience, and resource efficiency with IoT-based precision agriculture. *International Journal of Research and Review in Applied Science, Humanities, and Technology*, *2*, 172–179. https://doi.org/10.71143/7db36796

Khosravi Aqdam, K., Asadzadeh, F., Momtaz, H. R., Miran, N., & Zare, E. (2022). Digital mapping of soil erodibility factor in northwestern Iran using machine learning models. *Environmental Monitoring and Assessment*, *194*(5), 387. https://doi.org/10.1007/s10661-022-10048-1

Khosravi, I. (2025). Towards sustainable agriculture in Iran using a machine learning-driven crop mapping framework. *European Journal of Remote Sensing*, *58*, 2490787. https://doi.org/10.1080/22797254.2025.2490787

Kouakan Adanin, N. A., & Balungu, D. M. (2025). Predicting agricultural commodity stock prices: A comparison of statistical methods and machine learning algorithms. In *2025 IEEE Ural-Siberian Conference on Biomedical Engineering, Radioelectronics and Information Technology* (pp. 304–307). IEEE. https://doi.org/10.1109/USBEREIT65494.2025.11054062

Lakhiar, I. A., et al. (2024). A review of precision irrigation water-saving technology under changing climate for enhancing water use efficiency, crop yield, and environmental footprints. *Agriculture*, *14*(7), 1141. https://doi.org/10.3390/agriculture14071141

Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors*, *18*(8), 2674. https://doi.org/10.3390/s18082674

López-Martínez, M. de J., Díaz-Flórez, G., Villagrana-Barraza, S., Castañeda-Miranda, C. L., Solís-Sánchez, L. O., Ortiz-Esquivel, D. I., de la Rosa-Vargas, J. I., & Olvera-Olvera, C. A. (2024). Pattern classification of an onion crop (*Allium cepa*) field using convolutional neural network models. *Agronomy*, *14*(6), 1206. https://doi.org/10.3390/agronomy14061206

Manogna, R. L., Dharmaji, V., & Sarang, S. (2025). Enhancing agricultural commodity price forecasting with deep learning. *Scientific Reports*, *15*(1), 20903. https://doi.org/10.1038/s41598-025-05103-z

Matese, A., Czarnecki, J. M. P., Samiappan, S., & Moorhead, R. (2024). Are unmanned aerial vehicle-based hyperspectral imaging and machine learning advancing crop science? *Trends in Plant Science*, *29*(2), 196–209. https://doi.org/10.1016/j.tplants.2023.09.001

Mim, M., Sultana, F., & Hasan, M. (2025). AI-powered autonomous farming: The future of sustainable agriculture. *European Journal of Theoretical and Applied Sciences*, *3*(1), 11–31. https://doi.org/10.59324/ejtas.2025.3(1).02

Paul, R. K., Yeasin, M., Tamilselvi, C., Paul, A. K., Sharma, P., & Birthal, P. S. (2025). Can deep learning models enhance the accuracy of agricultural price forecasting? Insights from India. *Intelligent Systems in Accounting, Finance and Management*, *32*(1), e70002. https://doi.org/10.1002/isaf.70002

Pierre Nyakuri, J., Nkundineza, C., Gatera, O., & Nkurikiyeyezu, K. (2024). State-of-the-art deep learning algorithms for Internet of Things-based detection of crop pests and diseases: A comprehensive review. *IEEE Access*, *12*, 169824–169849. https://doi.org/10.1109/ACCESS.2024.3455244

Ruiz-Real, J. L., Uribe-Toril, J., Torres Arriaza, J. A., & de Pablo Valenciano, J. (2020). A look at the past, present, and future research trends of artificial intelligence in agriculture. *Agronomy*, *10*(11), 1839. https://doi.org/10.3390/agronomy10111839

Sami, S., Hajian, M., & Nazghelichi, T. (2026). A time-driven approach leveraging universally accessible features for photovoltaic power forecasting. *Iranica Journal of Energy & Environment*, *17*(2), 382–396. https://doi.org/10.5829/ijee.2026.17.02.13

Savary, S., Willocquet, L., Pethybridge, S. J., Esker, P., McRoberts, N., & Nelson, A. (2019). The global burden of pathogens and pests on major food crops. *Nature Ecology & Evolution*, *3*(3), 430–439. https://doi.org/10.1038/s41559-018-0793-y

Shaikh, F. K., Memon, M. A., Mahoto, N. A., Zeadally, S., & Nebhen, J. (2022). Artificial intelligence best practices in smart agriculture. *IEEE Micro*, *42*(1), 17–24. https://doi.org/10.1109/MM.2021.3121279

Shamshiri, R. R., Weltzien, C., Hameed, I. A., Yule, I. J., Grift, T. E., Balasundram, S. K., Pitonakova, L., Ahmad, D., & 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. https://doi.org/10.25165/ijabe.v11i4.4278

Silva, J. A. O. S., de Siqueira, V. S., Mesquita, M., Vale, L. S. R., da Silva, J. L. B., da Silva, M. V., Lemos, J. P. B., Lacerda, L. N., Ferrarezi, R. S., & de Oliveira, H. F. E. (2024). Artificial intelligence applied to support agronomic decisions for the automatic aerial analysis images captured by UAV: A systematic review. *Agronomy*, *14*(11), 2697. https://doi.org/10.3390/agronomy14112697

Simhadri, C. G., Kondaveeti, H. K., Vatsavayi, V. K., Mitra, A., & Ananthachari, P. (2025). Deep learning for rice leaf disease detection: A systematic literature review on emerging trends, methodologies and techniques. *Information Processing in Agriculture*, *12*(2), 151–168. https://doi.org/10.1016/j.inpa.2024.04.006

Talaviya, T., Shah, D., Patel, N., Yagnik, H., & Shah, M. (2020b). Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides. *Artificial Intelligence in Agriculture*, 4, 58–73. https://doi.org/10.1016/j.aiia.2020.04.002

Valin, H., Sands, R. D., van der Mensbrugghe, D., Nelson, G. C., Ahammad, H., Blanc, E., Bodirsky, B., Fujimori, S., Hasegawa, T., Havlík, P., Heyhoe, E., Kyle, P., Mason-D'Croz, D., Paltsev, S., Rolinski, S., Tabeau, A., van Meijl, H., von Lampe, M., & Willenbockel, D. (2014). The future of food demand: Understanding differences in global economic models. *Agricultural Economics*, *45*(1), 51–67. https://doi.org/10.1111/agec.12089

Wang, S., Xu, D., Liang, H., Bai, Y., Li, X., Zhou, J., Su, C., & Wei, W. (2025). Advances in deep learning applications for plant disease and pest detection: A review. *Remote Sensing*, *17*(4), 698. https://doi.org/10.3390/rs17040698

Younas, M., Akhtar, N., Batool, S., Owais, M., Sahar, S., & Anum, W. (2025). The integration of artificial intelligence in agriculture: Emerging trends, benefits and challenges. *Journal of Asian Development Studies*, *14*(1), 1316–1333. https://doi.org/10.62345/jads.2025.14.1.105

Zha, J. (2020). Artificial intelligence in agriculture. *Journal of Physics: Conference Series*, *1693*, 012058. https://doi.org/10.1088/1742-6596/1693/1/012058

Zhang, S., Xu, J., & Chung, K.-W. (2017). Desynchronization-based congestion suppression for a star-type internet system with arbitrary dimension. *Neurocomputing*, *266*, 42–55. https://doi.org/10.1016/j.neucom.2017.05.023

Zhang, T., & Tang, Z. (2024). Agricultural commodity futures prices prediction based on a new hybrid forecasting model combining quadratic decomposition technology and LSTM model. *Frontiers in Sustainable Food Systems*, *8*. https://doi.org/10.3389/fsufs.2024.1334098

Becerra-Encinales, D. (2024). Agricultural extension for adopting technological practices in developing countries: A scoping review of barriers and dimensions. *Sustainability*, *16*(9), 3555. https://doi.org/10.3390/su16093555