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AI-DRIVEN DEVICES IN CLIMATE-RESILIENT AGRICULTURE AND SUSTAINABLE FOOD SYSTEMS: LEVERAGING MACHINE LEARNING AND IoT FOR FUTURE-READY INNOVATIONS

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Abstract: Global agriculture and food security face significant challenges due to climate change, necessitating innovative and long-term solutions. When integrated with machine learning (ML) and the Internet of Things (IoT), AI-powered technologies can revolutionize the development of sustainable food systems and climate-resilient agriculture. Precision farming techniques that maximize resource use while reducing environmental effects, real-time monitoring of soil, water, and crop health, and predictive analytics for weather and yield forecasts are all made possible by these technologies. Big datasets are generated by IoT-enabled sensors, and ML models analyze them to create useful information for adaptive decision-making. Resilience to climatic variability and disruptions is strengthened through applications like supply chain optimization, advanced pest monitoring, and regulated watering. AI-driven technologies create opportunities for agricultural systems that are prepared for the future by increasing productivity, reducing waste, and encouraging environmentally sustainable practices. To ensure sustainability, resilience, and food security, this review article explores how AI, ML, and IoT could be integrated into agriculture.

Keywords: Agri-tech innovation, AI, Climate-resilient agriculture, Digital agriculture, Farming, IoT, ML.

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INTRODUCTION

The agricultural sector has significant problems due to the world's population expansion, which is expected to reach 9.7 billion individuals by 2050. These concerns are mostly related to sustainability and efficiency (Lal, 2016; Kumari *et al*., 2025). The increasing implications of climate change have faced agriculture with more difficulties in recent years (Arora, 2019). One of the most significant issues facing the world today appears to be climate change, which has a significant influence on rural lives, food security, biodiversity and agricultural output (Verma, 2021). Global temperature has increased by around 1.1°C over pre-industrial levels, according to the IPCC (Intergovernmental Panel on Climate Change), which has led to prolonged droughts, severe rainfall, and unpredictable weather patterns (Islam *et al*., 2022). The current farming practices are immediately affected by these climate changes due to shifts in crop growth cycles, soil fertility, and water availability, which decrease agricultural output and lead to food shortages (Zong *et al*., 2022). According to Chouhan *et* *al*. (2023), climate change has also increased the frequency and severity of natural disasters, such as heatwaves, hurricanes, and floods, which destroy farmlands and disrupt food supply systems. These notable changes in weather patterns raise concerns about the resilience of our agricultural systems and threaten the availability of food (Sakapaji, 2023).

Utilizing modern technology such as artificial intelligence (AI) can completely transform farming methods across the globe (Yu *et al*., 2021; Aijaz *et al*., 2025). With the development of integrated farm management, AI provides contemporary agriculture, and precision farming in particular, with new relevance (Fatima, 2025). Essential components of agricultural innovation include robots, drones, and automated surveillance systems. To optimize field management, drones can be utilized in sites for real-time monitoring by collecting airborne data to evaluate crop health and diagnose crop infections (Abbas *et al*., 2023). Therefore, these technologies promote precision farming by offering precise data that allows for well-informed decisions to be made about pest management, fertilizer usage, and irrigation.

The key climate variables, such as soil pH, ambient temperature, and precipitation, are further supported by AI in their research investigation (Zanobetti and O'Neill, 2018; Naz *et al*., 2022; Badugu *et al*., 2024; Lebu *et al*., 2024). AI-powered forecasting algorithms identify patterns in the weather, permitting farmers to take appropriate measures and lessen the adverse effects of severe weather. AI-powered precision agriculture uses data from aerial photographs and IoT sensors to identify the best conditions for grafting, watering, and harvesting cycles (Adinarayana *et al*., 2024).

Due to the widespread usage of AI because of its advancements, it decreased farmers' labour from planting seeds to harvesting crops. According to these assessments, using AI in agriculture has several chances for increased resource efficiency, waste minimization, and sustainable crop growth. These high-tech techniques and logics comprise artificial neural networks (ANN), expert systems, fuzzy logic, and neuro-fuzzy logic (Naqvi *et al*., 2025). However, by maximizing the use of resources like water, electricity, and fertilizers while protecting the environment, the IoT encourages environmentally friendly farming techniques that help to achieve sustainable goals (Khan *et al*., 2021; Gupta *et al*., 2026). IoT sensors are essential for tracking soil health and evaluating the effects of climate change on crop yields, enabling farmers to take action and improve crop resilience. Considering the above scenarios, the current review article was proposed to elaborate on the research gaps by utilizing the application of AI approaches in agriculture to combat climate change. It demonstrates how IoT and machine learning can work together to solve challenges, provide novel approaches, and make farming more sustainable for the future.

NECESSITY OF CLIMATE-RESILIENT AGRICULTURE TECHNIQUES

Climate-resilient farming methods can be used immediately to address the problems caused by climate change. To make crop production stronger against climate challenges, CRA (climate-resilient agriculture) is a comprehensive method that combines new technology, organic farming techniques, and legal measures (Fig. 1) (Hellin *et al*., 2023). In contrast to traditional mitigation strategies that only aim to reduce carbon emissions, CRA emphasizes improved soil quality, climate-tolerant crop production, and the efficient use of natural resources (Zuma *et al*., 2023).

Several adaptable strategies have been proposed to enhance the climate resilience in agriculture. Agroforestry, precision irrigation, integrated pest control, and sustainable agriculture are some of these practices that help preserve soil moisture, lower greenhouse gas emissions, and boost total output (Srivastava *et al*., 2024). According to Nyasimi *et al*. (2017), CRA approaches lay strong emphasis on sustaining rural communities by encouraging sustainable livelihoods and fair access to financing, extension services, and agricultural products. Climate change demands climate-resilient agriculture for sustainable food security. A safe and nourishing food supply for everyone can be maintained through climate-resilient farming, which helps farmers adapt to the impacts of climate change (FAO, 2020).

1. Precision Farming

A well-known use of AI is precision farming, which emerged with improved supervision over agricultural practices (Fig. 2) (Karunathilake *et al*., 2023). Global positioning system (GPS) and IoT devices are employed to the collect data from agricultural surroundings for precision farming (Singh *et al*., 2021). The basic aspect of precision farming is its ability to acquire data in real time using GPS and IoT devices for ongoing observation of variables, such as productivity of crops, weather conditions, and soil health (Ukhurebor *et al*., 2021). By minimizing the influence of agricultural practices on surface water and environment, precision farming additionally seeks to save essential resources, including groundwater (Lakhiar *et al*., 2024).

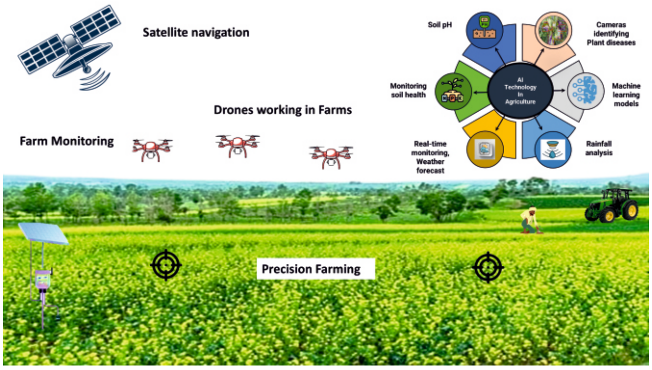

Fig. 1: Diagrammatic illustration of the integration of AI technologies into climate-resilient agriculture to improve long-term sustainability, crop yield, and resource efficiency.

2. Machine Learning (ML) Device

ML-developed devices offer a wide range of capabilities in forecasting, disease detection, and pest control, representing a significant advancement in agricultural technology (Pandey *et al*., 2022; Delfani *et al*., 2024). Both historical and current statistics can be analyzed by these devices to forecast agricultural production. The ML approaches might be used to optimize resources in addition to predictive analytics and crop disease control (Aijaz *et al*., 2025).

3. Agricultural Robotics

Agricultural robots boost the effectiveness of operations, decrease the need for human resource components, and automate labour-intensive tasks (Charania and Li, 2020; Wang *et al*., 2021). Robots with AI capabilities are being used for a variety of duties, including weeding and harvesting seeds. These self-sufficient devices are capable of highly accurate field navigation and round-the-clock operation in a variety of weather situations (Bilal *et al*., 2023; Moshayedi *et al*., 2024). In addition to expediting agricultural procedures, robots reduce human error and raise the general criteria for agricultural produce quality (Holm *et al*., 2024). By developing more intelligent, precise, and productive agricultural processes with reduced resource use, these AI techniques are revolutionizing farming practices. Such advancements have increasingly given food production an upgraded look.

4. Crop Monitoring

AI could be used to monitor diseases, pests, and other issues in crops. Drones with AI capabilities may fly over crops and analyze the photographs to look for indications of stress. Additionally, AI may be used to evaluate satellite data in order to monitor agricultural development and highlight regions that are vulnerable to drought or other unfavorable weather patterns (Minhans *et al*., 2025). The advanced tools now used in contemporary agriculture are thoroughly described in Table 1, together with their salient characteristics, uses, drawbacks, and challenges.

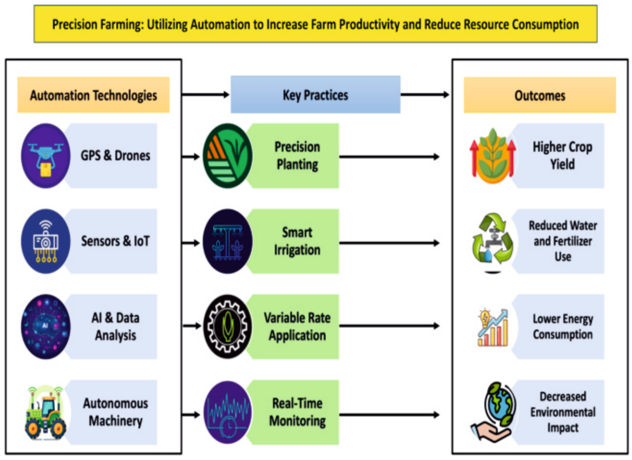

Fig. 2: A conceptual flow diagram of automation-driven precision farming techniques contributes to resource efficiency and sustainable development.

FUNCTION OF ML AND AI IN MANAGING CLIMATE ISSUES

Emerging technologies in AI and ML have brought about revolutionary approaches to climate-resilient agriculture, empowering farmers to lower climatic risks while simultaneously increasing output. Analytical prediction AI creates accurate climate predictions and early warnings for extreme weather occurrences by utilizing large datasets from satellite imaging, remote sensing, and IoT-enabled devices (Tan *et al*., 2022).

According to Nyasimi *et al*. (2017), these components help farmers make well-informed decisions on pest management techniques, watering requirements, and planting schedules, which lowers crop damage and boosts yield returns. Intelligent irrigation systems and automated soil sensors are examples of artificial intelligence-based precision agricultural technologies that are important tools for enhancing soil fertility management and water-use efficiency (Islam *et al*., 2022). By improving supply chain management and policy decision-making, AI advances global food safety beyond farm-level implementations. AI-powered market analysis tools evaluate supply and demand patterns, cost changes, and logistical effectiveness to maximize supply chain networks and minimize losses after harvest (Hellin *et al*., 2023). AI-powered farming policy models also help governments create evidence-based policies that promote sustainable land use management and climate adaptation (Aijaz *et al*., 2025).

Table 1: An overview of the innovative methods utilized currently in modern agricultural practices.

Technology	Utilization	Drawbacks and Challenges	References
Artificial intelligence (AI)	Analysis of soil health	Lack of dataset standardization	Rani *et al.* (2023); Espinel *et al.* (2024)
	Prediction of pests and diseases	Restrictions on real-time dataset access	
	Forecasting crop modelling	Close-range data collection	
	Automated equipment	Identifying minor symptoms	
		Variations in illumination and imaging quality	
		Disease progression and cross-class comparisons	
Deep learning (DL) and machine learning (ML) models	Automated harvesting and management	Limited datasets are the root cause of model failures; diverse, real-world field photos are essential.	Alibabaei *et al.* (2022)
	Forecasting crop	The kind and magnitude	
	yields	of input affect accuracy and execution time.	
	Identifying and controlling weeds	Expensive, time-consuming, specialized, and unsupervised methods need research.	
	Identifying diseases and pests	High computational/ deployment costs	
Internet of Things (IoT)	Measuring and controlling irrigation	Node capture and outages impair decision-making, precision, and data reliability.	Xu *et al.* (2022); Naseer *et al.* (2024)
	Assessing soil	Data transfer attacks result in stealing, spying, or bad agricultural choices.	
	Tracking humidity and temperature	IoT-based agriculture faces security risks from data collection, storage, processing, and transmission.	
	Air surveillance		
	Water evaluation		
	Disease control checking		

AI AND IoT INTEGRATION IN SMART FARMING

Smart farming involves the IoT and AI in cyber-physical systems to provide all-encompassing agricultural management (Sharma and Shivandu, 2024). A wide range of fields is covered by AI applications, including weed control, identifying diseases, crop health surveillance, and sustaining soils (Fig. 3). Prominent instances include fuzzy logic-based Soil Risk Characterization Decision Support Systems (SRCDSS), Management-Oriented Modeling (MOM), computer vision systems, Artificial Neural Networks (ANNs), Invasive Weed Optimization (IWO), and Support Vector Machines (SVMs) (Karunathilake *et al.*, 2023). For the enhancement of crop productivity, sustainability, and climate resilience in smart agricultural systems, a number of high-tech computational and decision-support tools have been developed to expand AI–IoT integration.

1. Irrigation Decision Support Systems: As per the reports of Rupnik *et al.* (2019), farmers are now totally dependent on smart agriculture, which mostly consists of decision support systems (DSS) that combine data and provide suggestions with accurate information. According to Simionesei *et al.* (2020), irrigation decision support systems (IDSS) have become an essential technology for facilitating data-driven control of irrigation. In order to enable optimal water usage, these systems incorporate real-time data on weather, soil moisture, and crop tolerance, which may be received via IoT sensors. Fuzzy logic has become more popular among the numerous soft computing approaches used in IDSS because of its capacity to deal with imprecise and unpredictable ideas.

2. Management-Oriented Modeling (MOM): An objective-based AI-based decision support system called Management-Oriented Modeling (MOM) generates, assesses, and enhances farming operation techniques, particularly for water and fertilizer (nitrogen) control (Li and Yost, 2000).

3. Artificial Neural Networks (ANNs): In the present scenario, artificial neural networks (ANNs) have become a potent tool for handling nonlinear issues related to the agriculture sector. These models depict hierarchical characteristics from the data and effectively handle nonlinear problems because they resemble the organization of the human nervous system (Castillo-Girones *et al.*, 2025). Some of the most common applications of ANNs comprise yield prediction (Gutiérrez *et al.*, 2019), soil management, precision spraying, crop identification (Xiao *et al.*, 2018), plant phenotyping (Song *et al.*, 2021), and early pest and disease detection (Polder *et al.*, 2019).

4. Convolutional Neural Networks (CNNs): Incorporating satellite and drone data, Convolutional Neural Networks (CNNs) provide precise crop monitoring, disease diagnosis, and stress evaluation, supporting climate-resilient agriculture (Sakka *et al.*, 2025). According to Sakthipriya and Naresh (2023), they improve yield prediction, resource optimization, and decision-making in favor of changing climate circumstances, all of which contribute to adaptive agricultural management. LeCun Convolutional Neural Network, Google Inception Network, Residual Neural Network, Mobile Convolutional Neural Network, Efficient Convolutional Neural Network, and You Only Look Once Object Detection Network are some of the CNN processing methods that are frequently utilized in agricultural and climate-resilient applications.

5. Invasive Weed Optimization (IWO): Invasive Weed Optimization (IWO) is a biological metaheuristic algorithm designed to tackle complex agricultural optimization issues by analyzing the competitive and adaptive reproductive behavior of invasive weeds (Misaghi and Yaghoobi, 2019). It is widely used in the farming sector for crop planning, irrigation scheduling, and fertilizer management to enhance production, improve sustainability, and increase resource efficiency.

6. Support Vector Machines (SVMs): Support Vector Machines (SVMs) consist of supervised machine

Table 2. Present Advances in Artificial Intelligence for Sustainable Agriculture (2021–2025).

Application Area in Agriculture	AI Techniques Used	Performance Highlights	Merits	References
Pest, Disease & Weed Monitoring	DL, Convolutional Neural Network (CNNs), YOLOv5, Attention-Based Models	F1 score >80% in field tests; accuracy >85% on public data sets.	Allows for the quick and accurate detection of weeds and crop pests; it also makes real-time monitoring and early response possible	Hoque and Padhiary (2024); Padhiary *et al.* (2025)
Crop Yield Forecasting	Hybrid ML + Biophysical Models, Long Short-Term Memory (LSTM), CNN-RNN)	90-99% forecast accuracy; wheat yield up to 99.9% R2; corn yield 92%	Improves decision assistance for managing crops under climate variability by integrating climatic, geographical, and temporal data.	Badshah *et al.* (2024); Dubey and Motwani (2024)
Irrigation & Input Management	Deep Reinforcement Learning, Decision Support Systems (DSS)	5-15% increase in yield; 25-40% decrease in water usage; and 30-40% less fertilizer.	Maximizes fertigation and irrigation techniques, lowers input costs, and encourages the sustainable use of resources.	Hoque and Padhiary (2024); Padhiary *et al.* (2025)
Digital Twin–Based Environmental Control	Digital Twin + Edge Computing	Improved precision of robotic navigation; better management of microclimate in controlled conditions.	Creates ongoing cyber-physical feedback loops and aids in smart farming operations and predictive maintenance.	Zhang *et al.* (2023); Pan *et al.* (2024)

learning algorithms that find the best hyperspace to optimize the margin across several data classes in classification and regression problems. Because of their high accuracy and robust performance with high-dimensional and non-linear databases, SVMs are frequently utilized in agriculture for forecasting crop yields, characterization of soil, disease detection, weed characterization, and remote sensing image processing of crops (Kok *et al.*, 2021).

Mobile automated systems, which allow farmers to utilize cell phones for activities like identifying diseases, recognizing species, and soil quality analysis using mobile applications, are an important use of AI. A network of linked gadgets and technology known as the IoT is essential to smart farming and precision agriculture. Drones, information and communication technology (ICT), and agricultural sensors are all integrated into IoT architecture in agriculture, which makes it easier to obtain crucial data for precision farming (Tomaszewski *et al.*, 2022). Table 2

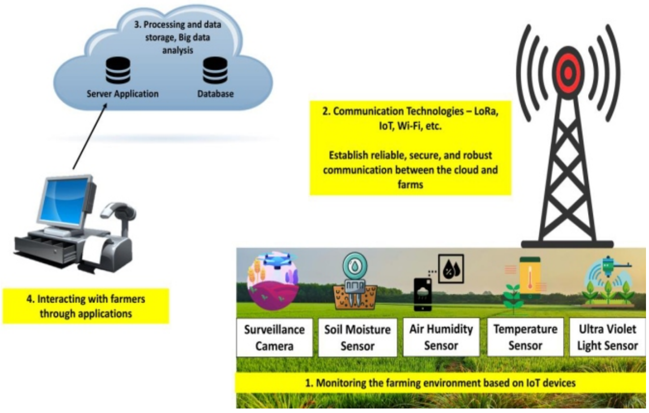

Fig. 3: Diagrammatic Illustration of ML/DL algorithms and IoT-enabled smart sensors working together to improve production, predictive analytics, and real-time crop monitoring.

RECENT ADVANCES IN AI FOR THE FOOD SYSTEMS AND AGRICULTURE SECTORS

AI is rapidly changing the agricultural industry, bringing with it an assortment of new ideas and developments that could totally transform farming practices (Oliveira and Silva, 2023; Liu *et al.*, 2023). AI-enabled crop monitoring has emerged as a crucial procedure (Oliveira and Silva, 2023). Drones powered by AI capture aerial photos of crops, permitting quick examination for indications of pests, diseases, or stress (Minhans *et al.*, 2025).

Furthermore, producers can pinpoint regions susceptible to unfavorable weather patterns and keep a close eye on crop growth via satellite imaging and AI data analysis, which improves resilience and maximizes production. Food supplies are carefully inspected by AI-powered cameras, which detect pest infestation and errors. The best foodstuffs available on the market are ensured by this technology.

AI additionally improves food safety regulations by analyzing sample foods for dangerous infectious diseases and germs (Dhal and Kar, 2025). AI also monitors how food items are moving through the supply chain, spotting possible obstacles and guaranteeing prompt, effective delivery. Beyond these particular patterns, AI is enabling farmers to make well-informed choices that minimize expenses and maximize resource utilization (Zatsu *et al.*, 2024). AI's capacity to identify the best times for fertilizing and irrigation minimizes fertilizer and water use while increasing agricultural yields. Furthermore, by identifying early indicators of pests or diseases, AI helps with agricultural management by enabling prompt actions that reduce crop damage (Minhans *et al.*, 2025). Larger-scale food waste is a major issue in the global food chain, and AI helps reduce it by forecasting demand for food goods and improving production and delivery patterns.

AI-DRIVEN INNOVATIONS FOR CLIMATE-RESILIENT AGRICULTURE IN INDIA

By encouraging climate resilience and resilient food systems, the application of AI, ML, and IoT technologies is transforming Indian agriculture. Precision farming is made possible by AI-driven equipment that analyzes soil, water, and crop conditions in real-time, enabling data-driven decision-making for maximum production (Nautiyal *et al.*, 2025). Although IoT-based sensors and drones improve irrigation effectiveness and lessen environmental effects, machine learning models aid in forecasting weather patterns, insect infestations, and yield patterns (Olawade *et al.*, 2024; Abdelmoneim *et al.*, 2025). These developments are vital in India, where farmer livelihoods and food security are seriously threatened by climatic variability. By decreasing input waste, increasing crop productivity, and lowering post-harvest losses, AI-powered solutions, including supply chain analytics, automated machinery, and smart irrigation systems, are promoting sustainable practices (Kumar *et al.*, 2024).

FUTURE PERSPECTIVES

In the present time, with the integration of AI-driven devices with machine learning and the Internet of Things, agriculture is currently quickly converting into a more data-driven, climate-resilient, and versatile system. As smart agricultural technologies expand, attention has switched to advanced digital techniques that enhance accountability, transparency, sustainability, and predictive capacity. In this context, a number of innovative strategies are becoming increasingly vital for developing the resilient and sustainable agri-food systems of the future:

1. **Explainable AI (XAI):** It improves the informed decision-making in agricultural areas by providing transparency without losing effectiveness (Pai *et al*., 2025). By developing techniques that make AI systems simpler for people to understand, dependable, and controllable, XAI aims to increase the accountability and transparency of AI (Moradi *et al*., 2024). With reliable learning performance and explainable models, XAI may emphasize the precise regions of a leaf picture that the model examines in plant disease diagnosis, assisting users in confirming that the system is concentrating on the right plant components. By ensuring accuracy and reliability across a variety of sustainable purposes, XAI principles aim to make AI understandable and reliable for people (Arrieta *et al*., 2020).

2. **Edge AI:** Edge AI reduces dependency on the centralized cloud systems by enabling real-time data processing directly on agricultural equipment, including IoT sensors, drones, and smart irrigation controls (Faye *et al*., 2025). Using locally deployed computer vision models, edge-enabled drones, and video sensors may identify symptoms of crop or pest infestation, stress, or nutritional deficiencies in plants. Fast inference with low power consumption is made possible by models such as YOLOv5-Tiny (Jarroudi *et al*., 2024). It promotes quick decision-making under dynamic climatic situations by reducing latency and enhancing response time.

3. **Federated learning (FL):** Decentralized machine learning is called federated learning. In FL, numerous customers can train a common model without exchanging local data (Hiremani *et al*., 2025). In rural agricultural regions with weak connections, adopting FL enhances data privacy and lowers latency problems (Elijah *et al*., 2018). Because IoT technologies enable real-time analysis and decision-making on any data, their applications in precision agriculture increase applicability (Weiss *et al*., 2019).

4. **Climate-risk digital twins:** Climate-risk digital twins are virtual representations of agricultural systems that replicate extreme weather, climatic variability, and field conditions in real time (Purcell and Neubauer, 2023). They make it possible for farmers to analyze risks and evaluate adaptive plans before deployment by combining sensor data, climate models, and predictive analytics (Jones *et al*., 2020).

CONCLUSIONS

In conclusion, by ensuring real-time monitoring, predictive analytics, and precise input management, AI-driven devices combined with machine learning and IoT greatly enhance climate-resilient agriculture. The outcome of the research include increased agricultural yield, efficient use of fertilizer and water, less environmental impact, and better ability to react to climatic changes. Overall, by enhancing resilience, resource efficiency, and long-term agricultural sustainability, AI-enabled technologies support sustainable food systems.

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