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Artificial Intelligence for climate-smart agriculture: A systematic review of applications, sustainability impacts, and future directions

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Abstract

Artificial Intelligence (AI) is rapidly transforming modern agriculture by enabling climate-smart practices that enhance productivity, resilience, and environmental sustainability. This systematic review examines the diverse applications of AI in climate-smart agriculture (CSA), focusing on technologies such as machine learning, deep learning, robotics, Internet of Things (IoT), remote sensing, and big data analytics. AI-driven systems have demonstrated significant potential in optimizing resource use efficiency, reducing greenhouse gas emissions, minimizing chemical inputs, and supporting climate adaptation strategies under changing environmental conditions. Furthermore, the review highlights the role of AI in promoting sustainable agricultural intensification, improving decision-making processes, and strengthening food security. Despite these advantages, several challenges remain, including high implementation costs, limited digital infrastructure, data privacy concerns, lack of technical expertise, and unequal technology accessibility among smallholder farmers. The study also identifies emerging trends such as explainable AI, AI-integrated digital twins, blockchain-enabled agricultural systems, and autonomous farming technologies. Overall, this review emphasizes that AI has the potential to become a cornerstone of sustainable and climate-resilient agriculture, provided that future research, policy support, and technological innovations address existing socioeconomic and ethical barriers.

Keywords: Artificial intelligence, climate-smart agriculture, precision farming, machine learning and sustainable crop production

Introduction

Agriculture is confronting unprecedented challenges due to climate change, population growth, natural resource degradation, and increasing food demand. The global population is expected to approach 10 billion by 2050, significantly intensifying pressure on food production systems and natural resources (FAO, 2023) [3]. Simultaneously, agriculture remains highly vulnerable to rising temperatures, irregular precipitation patterns, droughts, floods, and emerging pest and disease outbreaks (Challinor *et al.*, 2014) [1]. These climatic disturbances threaten crop productivity, soil fertility, water availability, and overall food security, particularly in developing countries where farming systems are highly climate-sensitive. In addition, agriculture contributes substantially to greenhouse gas emissions and freshwater consumption, emphasizing the urgent need for sustainable and resilient production systems (IPCC, 2022; Zhao *et al.*, 2017) [4, 8].

Climate-Smart Agriculture (CSA) has emerged as an integrated approach to address these interconnected challenges by enhancing productivity, strengthening climate resilience, and reducing environmental impacts (FAO, 2010) [2]. Practices such as precision irrigation, conservation agriculture, integrated nutrient management, and climate-resilient cropping systems have demonstrated considerable potential for sustainable agricultural development (Smith *et al.*, 2008) [7]. However, the effective implementation of CSA requires accurate monitoring, predictive analysis, and data-driven decision-making systems.

Recent advancements in Artificial Intelligence (AI) have created transformative opportunities

for modern agriculture. Technologies including machine learning, deep learning, Internet of Things (IoT), robotics, remote sensing, and big data analytics enable real-time crop monitoring, disease detection, yield forecasting, and optimized resource management (Liakos *et al.*, 2018; Kamilaris & Prenafeta-Boldú, 2018) ^[6, 5]. AI-driven systems improve agricultural efficiency, minimize resource wastage, and support climate adaptation strategies.

Concept and Components of Climate-Smart Agriculture
Definition and Principles of Climate-Smart Agriculture

Climate-Smart Agriculture (CSA) is an integrated approach designed to address the interconnected challenges of food security, climate change, and environmental sustainability. The Food and Agriculture Organization (FAO) defines CSA as an agricultural framework that aims to sustainably increase productivity, strengthen resilience and adaptation to climate change, and reduce greenhouse gas emissions wherever feasible (FAO, 2010; Lipper *et al.*, 2014) ^[2, 10]. Unlike conventional agricultural systems focused primarily on yield maximization, CSA promotes sustainable resource management, ecosystem conservation, and long-term agricultural resilience. The core principles of CSA include sustainability, resilience, resource-use efficiency, and integrated farm management. Practices such as conservation agriculture, agroforestry, crop diversification, integrated nutrient management, and precision irrigation improve soil health, conserve water resources, and enhance climate resilience (Tilman *et al.*, 2011; Wezel *et al.*,

2020) ^[13, 15]. CSA also emphasizes equitable access to technologies and climate information, particularly for smallholder farmers who are highly vulnerable to climate variability (Vermeulen *et al.*, 2012) ^[14].

Pillars of Climate-Smart Agriculture

CSA is structured around three interconnected pillars: productivity, adaptation, and mitigation. The productivity pillar focuses on sustainable intensification to improve crop yields and farm income while minimizing environmental degradation (Garnett *et al.*, 2013) ^[9]. The adaptation pillar aims to enhance resilience against climate-related stresses such as droughts, floods, and heat stress through climate-resilient crops, agroforestry, and efficient water management (Thornton *et al.*, 2014) ^[12]. The mitigation pillar emphasizes reducing greenhouse gas emissions through conservation agriculture, efficient nutrient management, and carbon sequestration practices (Smith *et al.*, 2020) ^[11].

Importance of Climate-Smart Agriculture

CSA contributes significantly to sustainable development by improving food security, conserving natural resources, and supporting climate action. It aligns closely with several Sustainable Development Goals (SDGs), including Zero Hunger, Clean Water, Climate Action, and Life on Land (FAO, 2023) ^[3]. By integrating productivity, resilience, and environmental sustainability, CSA provides a comprehensive pathway toward resilient and sustainable agricultural systems.

Table 1: Alignment of Climate-Smart Agriculture Pillars with Selected Sustainable Development Goals.

CSA Pillar	Key Practices	Primary SDGs Addressed	Key Environmental Benefit	Key Socioeconomic Benefit	References
Productivity	Precision nutrition, SRI, integrated soil fertility management, legume intercropping	SDG 2, SDG 12	Reduced input use; lower eutrophication risk	Increased farm income; improved food & nutrition security	FAO (2010) ^[2] ; Liakos <i>et al.</i> (2018) ^[6]
Adaptation	Drought-tolerant varieties, agroforestry, AWD, index insurance, seasonal forecasting	SDG 2, SDG 6, SDG 13, SDG 15	Ecosystem service maintenance; biodiversity conservation	Reduced production risk; stabilized household income	Challinor <i>et al.</i> (2014) ^[1] ; IPCC (2022) ^[4]
Mitigation	Conservation agriculture, enhanced-efficiency fertilizers, biochar, agroforestry, manure management	SDG 13, SDG 15, SDG 12	GHG emission reduction; soil carbon sequestration	Carbon market revenue potential; long-term soil productivity	Smith <i>et al.</i> (2008) ^[7] ; Poepflau & Don (2015)

Artificial Intelligence Technologies in Agriculture

Artificial Intelligence (AI) has emerged as a transformative technology in modern agriculture, supporting the transition from conventional farming to precision and climate-smart agricultural systems. AI integrates technologies such as Machine Learning (ML), Deep Learning (DL), Internet of Things (IoT), robotics, big data analytics, and cloud computing to improve productivity, resource-use efficiency, and sustainability (Bhat & Huang, 2021; Javaid *et al.*, 2022) ^[17, 20]. These technologies enable data-driven decision-making for irrigation management, disease detection, crop monitoring, yield prediction, and supply chain optimization. Machine Learning algorithms are widely used for predictive analysis, crop yield forecasting, soil fertility assessment, and pest detection. Techniques such as Random Forest, Support Vector Machines, and Artificial Neural Networks help optimize agricultural inputs and improve farm management practices (Liakos *et al.*, 2018) ^[6]. Deep Learning models, particularly

Convolutional Neural Networks (CNNs), have shown high accuracy in image-based disease detection, weed identification, and crop monitoring using drone and satellite imagery (Mohanty *et al.*, 2016) ^[21]. The Internet of Things (IoT) enables real-time monitoring of soil moisture, temperature, humidity, and crop health through interconnected sensors and smart devices (Ayaz *et al.*, 2019) ^[16]. Similarly, robotics and automation technologies, including autonomous tractors, drones, and robotic harvesters, reduce labor dependency and enhance operational precision in farming systems (Duckett *et al.*, 2018) ^[19]. Big data analytics and cloud computing further strengthen smart agriculture by integrating large agricultural datasets for predictive modeling, climate forecasting, and decision support systems (Coble *et al.*, 2018) ^[18]. Overall, AI-driven technologies are significantly improving agricultural efficiency, sustainability, and resilience, making them essential components of future climate-smart food systems.

Table 2: Definitions and Concepts of AI Technologies

AI Technology	Definition / Concept	Key Sub-components	References
Machine Learning (ML)	Computational systems that learn patterns from data without being explicitly programmed, enabling predictive analysis and decision-making in agriculture.	SVM, Random Forest, Decision Trees, ANN	Liakos <i>et al.</i> (2018) ^[6] ; Russell & Norvig (2020)
Deep Learning (DL)	A subset of ML using multi-layered neural networks for complex image recognition, pattern detection, and time-series forecasting in crop systems.	CNN, RNN, LSTM	LeCun <i>et al.</i> (2015); Kamilaris & Prenafeta-Boldú (2018) ^[5]
Internet of Things (IoT)	Network of interconnected sensors and smart devices that collect and exchange real-time agricultural data through internet-based communication systems.	Soil sensors, wearable devices, smart meters	Ayaz <i>et al.</i> (2019) ^[16] ; Wolfert <i>et al.</i> (2017) ^[24]
Remote Sensing & UAVs	Satellite and drone-based technologies that capture multispectral, thermal, and hyperspectral imagery for large-scale crop and environmental monitoring.	NDVI, thermal imaging, LiDAR	Shamshiri <i>et al.</i> (2018); Pathak <i>et al.</i> (2019) ^[25]
Big Data Analytics	Processing and analysis of large, heterogeneous agricultural datasets from sensors, satellites, and machinery to extract actionable management insights.	Predictive analytics, cloud storage, data mining	Coble <i>et al.</i> (2018) ^[18] ; Bhat & Huang (2021) ^[17]
Robotics & Automation	AI-guided autonomous machines that perform precise, repetitive farm tasks including planting, weeding, spraying, and harvesting without human intervention.	Agribots, autonomous tractors, robotic harvesters	Duckett <i>et al.</i> (2018) ^[19] ; Bechar & Vigneault (2016)

Table 3: Applications of AI in Different Crops

Crop	AI Technology Used	Application Area	Key Outcome	References
Wheat	CNN, Remote Sensing	Disease detection, yield prediction	Early disease diagnosis, reduced pesticide use	Mohanty <i>et al.</i> (2016) ^[21] ; Liakos <i>et al.</i> (2018) ^[6]
Rice	LSTM, IoT sensors	Irrigation scheduling, growth monitoring	Water savings of 15–30%, reduced CH ₄ emissions	Namin <i>et al.</i> (2018) ^[22] ; Talaviya <i>et al.</i> (2020) ^[23]
Maize	ML models, UAV imagery	Yield forecasting, stress detection	Improved yield accuracy, early drought response	Kim <i>et al.</i> (2020); Shamshiri <i>et al.</i> (2018)
Tomato	Deep learning, image recognition	Disease and pest detection, quality grading	Reduced crop losses, enhanced market quality	Mohanty <i>et al.</i> (2016) ^[21] ; Kamilaris & Prenafeta-Boldú (2018) ^[5]
Soybean / Legumes	Random Forest, satellite data	Nutrient management, soil fertility mapping	Reduced fertilizer use, improved NUE	Liakos <i>et al.</i> (2018); Bhat & Huang (2021) ^[17]
Fruits (general)	Robotic vision, CNN	Automated harvesting, ripeness detection	Reduced labor cost, minimized post-harvest losses	Duckett <i>et al.</i> (2018) ^[19] ; Bechar & Vigneault (2016)

Table 4: Benefits and Limitations of AI in CSA

Domain	Benefits	Limitations	References
Crop Productivity	Precision management raises yields; early warning reduces losses from pests and drought	Benefits not always replicated in smallholder or low-resource contexts	Liakos <i>et al.</i> (2018) ^[6] ; Javaid <i>et al.</i> (2022) ^[20]
Resource Efficiency	Optimized water, fertilizer, and pesticide use reduces input waste and environmental pollution	High equipment and software costs; variable ROI across farm scales	Talaviya <i>et al.</i> (2020) ^[23] ; Ayaz <i>et al.</i> (2019) ^[16]
Climate Adaptation	AI forecasting improves response to weather variability, drought, and extreme events	Model accuracy depends on data quality and regional calibration; poor internet limits real-time use	Namin <i>et al.</i> (2018) ^[22] ; Kim <i>et al.</i> (2020)
GHG Mitigation	Precision inputs reduce N ₂ O and CO ₂ emissions; soil carbon monitoring supports sequestration	Carbon monitoring tools require ground-truthing; adoption in developing countries remains low	Coble <i>et al.</i> (2018) ^[18] ; Javaid <i>et al.</i> (2022) ^[20]
Digital Infrastructure	Cloud platforms and mobile advisory tools extend reach of scientific knowledge to remote farmers	Rural connectivity gaps, digital illiteracy, and cybersecurity concerns hinder deployment	Wolfert <i>et al.</i> (2017) ^[24] ; Shamshiri <i>et al.</i> (2018)
Equity & Access	Low-cost mobile tools democratize advisory services; DSS bridges knowledge gaps for smallholders	Digital divide widens inequality between commercial and subsistence farmers	Pathak <i>et al.</i> (2019) ^[25] ; Bhat & Huang (2021) ^[17]

Table 5: Research Gaps and Future Directions

Research Gap	Current Limitation	Suggested Future Direction	References
Smallholder AI adoption	Most AI tools designed for large-scale commercial farming; limited use in resource-poor settings	Develop low-cost, offline-capable AI tools adapted for smallholder farming systems in developing countries	Pathak <i>et al.</i> (2019) ^[25] ; Javaid <i>et al.</i> (2022) ^[20]
Explainability of AI models	Deep learning models function as black boxes; farmers and policymakers cannot interpret recommendations	Integrate Explainable AI (XAI) frameworks into agricultural decision-support tools to improve transparency and trust	Arrieta <i>et al.</i> (2020) ^[26] ; Verdouw <i>et al.</i> (2021) ^[27]
Data standardization	Agricultural data is fragmented, region-specific, and lacks interoperability across platforms and institutions	Establish open, standardized agri-data frameworks and international data-sharing protocols for AI model training	Wolfert <i>et al.</i> (2017) ^[24] ; Coble <i>et al.</i> (2018) ^[18]
AI-blockchain	Supply chain traceability and carbon credit	Combine AI analytics with blockchain for	Lin <i>et al.</i> (2021);

integration	verification lack tamper-proof, decentralized systems	transparent carbon accounting, food traceability, and smart contract execution	Verdouw <i>et al.</i> (2021) ^[27]
Digital twin technology	Virtual farm simulation is not yet widely operationalized for real-time climate scenario planning	Scale digital twin platforms to field level for predictive crop management and climate adaptation planning	Verdouw <i>et al.</i> (2021) ^[27] ; Shamshiri <i>et al.</i> (2018)
Long-term sustainability evidence	Most AI-in-agriculture studies are short-term trials; longitudinal sustainability outcomes remain under-documented	Fund long-term, multi-site field trials to evaluate AI-CSA interventions across soil types, climates, and farming scales	Liakos <i>et al.</i> (2018) ^[6] ; Bhat & Huang (2021) ^[17]

Applications of Artificial Intelligence in Climate-Smart Agriculture

Artificial Intelligence (AI) has become a central component of climate-smart agriculture by improving productivity, enhancing resource-use efficiency, and strengthening the resilience of agricultural systems against climate variability. The integration of AI with precision farming technologies, remote sensing, robotics, and predictive analytics is transforming conventional agricultural practices into intelligent and data-driven systems. AI-based tools enable farmers to optimize irrigation, nutrient management, pest and disease control, crop forecasting, and greenhouse management while minimizing environmental impacts and conserving natural resources (Javaid *et al.*, 2022; Wolfert *et al.*, 2017)^[20, 24].

AI-Based Precision Irrigation

Water scarcity and irregular rainfall patterns caused by climate change have increased the importance of precision irrigation technologies in agriculture. AI-driven smart irrigation systems use sensors, machine learning algorithms, weather forecasts, and real-time soil moisture data to regulate water application according to crop requirements. These systems improve water-use efficiency and reduce water wastage by delivering precise quantities of irrigation at the appropriate time (Talaviya *et al.*, 2020)^[23].

AI-assisted irrigation scheduling helps farmers manage drought conditions more effectively by predicting crop water stress and evapotranspiration rates. Smart irrigation technologies integrated with IoT devices can automatically control irrigation pumps and valves, reducing labor requirements and operational costs. Such technologies are particularly valuable in arid and semi-arid regions where water conservation is essential for sustainable crop production (Ayaz *et al.*, 2019)^[16].

Table 1: AI Technologies Used in Precision Irrigation

Technology	Application	Benefits
Soil moisture sensors	Real-time soil water monitoring	Efficient water management
IoT-based irrigation systems	Automated irrigation scheduling	Reduced water wastage
Machine learning models	Prediction of crop water requirement	Improved irrigation accuracy
Weather forecasting systems	Drought and rainfall prediction	Better climate adaptation
Drone-based thermal imaging	Detection of water stress	Early stress management

Benefits of AI-Driven Climate-Smart Agriculture

Artificial Intelligence (AI)-driven climate-smart agriculture offers significant benefits for improving agricultural productivity, sustainability, and resilience under changing climatic conditions. The integration of AI technologies such as machine learning, deep learning, Internet of Things (IoT), robotics, and remote sensing enables data-driven farm management and precision agriculture practices (Javaid *et al.*, 2022; Wolfert *et al.*, 2017)^[20, 24]. These technologies support

efficient decision-making related to irrigation, nutrient management, disease detection, and crop monitoring.

One of the major advantages of AI in agriculture is enhanced productivity and resource-use efficiency. AI-based predictive models optimize irrigation scheduling, fertilizer application, and pest management, leading to higher crop yields and reduced input wastage (Liakos *et al.*, 2018)^[6]. Precision irrigation systems integrated with IoT sensors improve water-use efficiency, while site-specific nutrient management reduces excessive fertilizer use and environmental pollution (Talaviya *et al.*, 2020)^[23].

AI technologies also strengthen climate resilience by providing accurate weather forecasting and early warning systems for droughts, floods, and pest outbreaks. Predictive analytics help farmers adopt timely adaptation strategies, improving farm resilience against climate variability (Namin *et al.*, 2018)^[22]. In addition, AI-supported conservation practices contribute to greenhouse gas mitigation through optimized input use, reduced energy consumption, and improved soil carbon sequestration (Coble *et al.*, 2018)^[18].

Economically, AI-driven systems reduce labor dependency, lower production costs, and improve operational efficiency through automation and smart advisory services. These benefits collectively enhance farm profitability, food security, and long-term agricultural sustainability (Kamilaris & Prenafeta-Boldú, 2018)^[5].

Challenges and Limitations of AI-Driven Climate-Smart Agriculture

Despite its significant potential, the adoption of AI-driven climate-smart agriculture faces several economic, technical, and social challenges. One of the primary limitations is the high initial investment required for AI technologies such as sensors, drones, robotics, and automated irrigation systems, which restricts adoption among smallholder and resource-poor farmers (Pathak *et al.*, 2019)^[25]. In addition, inadequate digital infrastructure, including poor internet connectivity and unreliable electricity supply in rural areas, limits the effective implementation of IoT and cloud-based agricultural systems (Ayaz *et al.*, 2019)^[16].

Data-related challenges also hinder AI applications in agriculture. AI models require large volumes of accurate and real-time data; however, agricultural datasets are often fragmented, inconsistent, and region-specific, affecting prediction accuracy and decision-making efficiency (Wolfert *et al.*, 2017)^[24]. Limited digital literacy, lack of technical expertise, and insufficient training opportunities among farmers further constrain technology adoption, particularly in developing countries (Javaid *et al.*, 2022)^[20].

Ethical concerns related to data privacy, cybersecurity, and ownership of agricultural information have also emerged as critical issues in AI-based farming systems. Furthermore, excessive dependence on automated technologies may reduce human participation in agricultural decision-making processes. Therefore, strengthening rural digital infrastructure, improving

farmer training programs, ensuring affordable access to technologies, and developing effective data governance frameworks are essential for promoting inclusive and sustainable adoption of AI-driven climate-smart agriculture.

Artificial Intelligence (AI) is transforming climate-smart agriculture by improving productivity, resource-use efficiency, and environmental sustainability. Technologies such as machine learning, deep learning, IoT, robotics, remote sensing, and big data analytics enable precision farming practices that support efficient irrigation, nutrient management, crop monitoring, disease detection, and yield prediction (Liakos *et al.*, 2018; Javaid *et al.*, 2022) ^[6, 20]. These innovations strengthen agricultural resilience against climate variability while reducing environmental impacts and greenhouse gas emissions.

AI-driven systems also enhance decision-making through predictive analytics and real-time monitoring, supporting sustainable and climate-resilient agricultural production. Emerging technologies including explainable AI, blockchain integration, and digital twins are expected to further improve transparency, efficiency, and adaptability in future farming systems (Verdouw *et al.*, 2021) ^[27].

However, several barriers continue to limit large-scale adoption, particularly in developing countries. High implementation costs, inadequate digital infrastructure, limited technical expertise, and data privacy concerns remain major challenges (Arrieta *et al.*, 2020) ^[26]. Addressing these limitations will require strong policy support, investment in rural digital infrastructure, farmer training programs, and affordable technological solutions.

Overall, AI-driven climate-smart agriculture offers a promising pathway toward resilient, sustainable, and intelligent food production systems. Continued innovation, interdisciplinary research, and collaborative institutional efforts will be essential for ensuring global food security and sustainable agricultural development under changing climatic conditions.

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