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Artificial Intelligence for Climate-Smart Agriculture: A Review of Applications in Yield Prediction, Weather Forecasting, Irrigation Management and Pest and Disease Detection

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Abstract: Climate change is increasingly disrupting agricultural systems worldwide through more frequent extreme weather events, shifting rainfall patterns, and rising temperatures. These changes contribute to reduced crop yields, unstable food supplies, and heightened production risks, especially in vulnerable developing regions. In response, Climate-Smart Agriculture (CSA) has been developed as a strategic framework to improve agricultural productivity while enhancing resilience and promoting environmentally sustainable farming practices. Within this framework, Artificial Intelligence (AI) is increasingly recognized as a transformative tool capable of supporting data-driven agricultural decision-making. This review systematically synthesizes recent literature on AI applications in CSA, focusing on four key thematic areas: crop yield prediction, weather and climate forecasting, irrigation and water management, and pest and disease detection under climate stress. Peer-reviewed articles published between 2020 and 2026 were retrieved from Google Scholar, Semantic Scholar, and Crossref. A total of 170 studies were initially identified, of which 58 highly relevant articles were selected following screening based on relevance, quality, and thematic alignment. Findings indicate that AI-based systems significantly improve predictive accuracy, optimize resource use, and enhance early warning capabilities across agricultural systems. Machine learning, deep learning, remote sensing, IoT, and big data analytics are widely applied to support precision agriculture and climate adaptation strategies. However, key challenges such as data scarcity in developing regions, high implementation costs, limited farmer adoption, and climate uncertainty continue to constrain widespread adoption. The review concludes that AI holds strong potential to transform CSA by improving productivity, resilience, and sustainability. Nonetheless, its effectiveness depends on the development of accessible, affordable, and context-specific solutions supported by strong policy frameworks and improved digital infrastructure.

Keywords: *Machine Learning; Remote Sensing; Climate Resilience; Digital Infrastructure*.

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I. INTRODUCTION

Climate change has become one of the most critical global challenges affecting agricultural productivity, food security, and environmental sustainability. Rising temperatures worldwide, irregular rainfall, prolonged droughts, flooding events, heat stress, declining soil quality, and increasing outbreaks of pests and diseases are placing significant pressure on agricultural systems across the globe.

These climate-related changes are undermining crop productivity, lowering farmers' incomes, and worsening the vulnerability of rural communities, particularly in developing nations where farming systems rely largely on rainfall. (Zheng et al., 2024; Ali et al., 2025; Bara et al., 2025). Agriculture is therefore facing significant pressure to meet the food demands of a growing global population while adapting to unprecedented climate-related risks and minimizing environmental impacts. To address these growing challenges, Climate-Smart Agriculture (CSA) has gained attention as a sustainable strategy for improving agricultural productivity, strengthening resilience and adaptation to climate change, and lowering greenhouse gas emissions where feasible (Zheng et al., 2024; Attipoe, 2026). CSA integrates modern technologies, sustainable farming practices, and data-driven decision-making processes to improve agricultural sustainability under changing climatic conditions. However, the complexity and unpredictability of climate change require more advanced and intelligent systems capable of supporting farmers and policymakers with timely and accurate information.

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Artificial Intelligence (AI) is increasingly being recognized as a transformative technology with the potential to address several challenges in climate-smart agriculture through computer systems and algorithms that mimic human intelligence by learning, reasoning, predicting outcomes, and supporting decision-making processes. Technologies such as machine learning, deep learning, computer vision, robotics, remote sensing, big data analytics, and the Internet of Things (IoT) are increasingly being integrated into agricultural systems to improve efficiency, productivity, and sustainability (Masasi et al., 2024; Benos et al., 2021; Islam et al., 2024). AI technologies are capable of analyzing large and complex agricultural datasets more effectively than conventional analytical approaches, thereby enhancing precision agriculture and supporting climate adaptation efforts.

One important application of AI in climate-smart agriculture is crop yield prediction. Accurate crop yield forecasting plays a critical role in food security planning, market stabilization, supply chain coordination, and farm management decisions. However, conventional yield prediction approaches often face limitations in capturing the complex relationships among climatic, environmental, and agronomic factors. In contrast, AI-driven models, especially machine learning and deep learning techniques, have demonstrated improved predictive performance by integrating diverse data sources such as satellite imagery, weather information, soil properties, and vegetation indices (Jabed & Murad, 2024; Shawon et al., 2024; Gadhiya, 2025). These technologies enable farmers and policymakers to better anticipate production outcomes and climate-related risks.

AI is also increasingly applied in weather and climate forecasting within agricultural systems. Climate variability and extreme weather events continue to pose major threats to agricultural production because farming decisions are highly dependent on weather conditions. AI-enhanced climate models can analyze large climatic datasets to generate more accurate weather forecasts and climate predictions. These predictive systems help farmers optimize planting dates, harvesting schedules, fertilizer application, and other farm management practices while reducing exposure to climate risks (Masasi et al., 2024; Ali et al., 2025). Improved climate forecasting therefore contributes significantly to agricultural resilience and adaptation planning.

Another major area where AI contributes to climate-smart agriculture is irrigation and water management. Climate change has intensified water scarcity in many agricultural regions, increasing the need for efficient water utilization. AI-powered smart irrigation systems utilize machine learning algorithms, soil sensors, weather information, and IoT devices to determine optimal irrigation timing and water requirements (Bwambale et al., 2022; Talaviya et al., 2020; Hamdaoui et al., 2024). These systems improve water-use efficiency, reduce production costs, minimize water wastage, and enhance crop productivity under drought and water-limited conditions. AI-driven irrigation technologies therefore play a crucial role in promoting sustainable water management in agriculture.

Similarly, AI has demonstrated substantial potential in pest and disease detection under climate stress. Climate change has contributed to the increased spread and severity of crop pests and diseases due to changing environmental conditions. AI technologies such as computer vision, image recognition, drones, and deep learning models are increasingly being used for early pest and disease diagnosis (Ahmad et al., 2023; Delfani et al., 2024; Valleggi & Stefanini, 2024). Early detection enables farmers to implement timely control measures, reduce crop losses, minimize excessive pesticide use, and improve agricultural sustainability. AI-based monitoring systems therefore enhance both productivity and environmental protection within climate-smart agricultural systems.

Beyond these applications, AI technologies are increasingly being integrated with precision agriculture tools such as unmanned aerial vehicles (UAVs), robotics, and remote sensing technologies to improve farm monitoring and decision-making processes (Boursianis et al., 2022; Xiao et al., 2023; Mat Pauzi et al. 2025). The integration of AI with IoT technologies further supports smart farming systems capable of real-time monitoring, automated responses, and efficient resource management (Bara et al., 2025). These advancements demonstrate the growing importance of AI in transforming global agricultural systems toward sustainability and resilience.

Despite the considerable potential of AI in improving productivity, climate adaptation, resource management, and decision-making within climate-smart agriculture, its widespread adoption remains constrained by challenges such as weak technological infrastructure, limited technical expertise, unreliable internet connectivity, data privacy concerns, high implementation costs, and inadequate policy support, particularly in developing countries (Javaid et al., 2022; Wei et al., 2024). In addition, many existing studies focus on specific AI applications without providing a broader understanding of how AI technologies collectively contribute to climate-smart agriculture from a global perspective.

Against this background, this review aims to examine the applications of artificial intelligence in climate-smart agriculture from a global perspective. Specifically, the review focuses on four major thematic areas: AI in crop yield prediction, AI in weather and climate forecasting, AI for irrigation and water management, and AI for pest and disease detection under climate stress. The review further synthesizes current technological developments, opportunities, challenges, and future research directions associated with AI-driven agricultural innovations in promoting sustainable and resilient food systems.

The relevance of this topic extends to farmers, researchers, governments, agricultural industries, and global development agencies. AI-driven climate-smart agricultural systems can help farmers improve productivity, reduce climate-related risks, optimize resource utilization, and enhance farm profitability. For policymakers and development institutions, understanding the role of AI in agriculture is important for designing effective agricultural policies, climate adaptation strategies, and sustainable food

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security interventions. More broadly, the integration of AI into climate-smart agriculture has significant implications for environmental sustainability, economic development, and global food security in the face of increasing climate change challenges. Overall, the literature shows that AI applications in agriculture are broadly categorized into four main domains, each contributing to improved decision-making, efficiency, and sustainability in farming systems.

II. CONCEPTUAL FRAMEWORK AND SYNTHESIS OF REVIEWED LITERATURE

To synthesize the diverse body of research analyzed throughout this review, this section establishes a unified conceptual framework. By anchoring the findings of the reviewed literature into distinct visual pathways, this framework maps how current research connects high-level agricultural themes, technical data pipelines, and ultimate socio-economic outcomes.

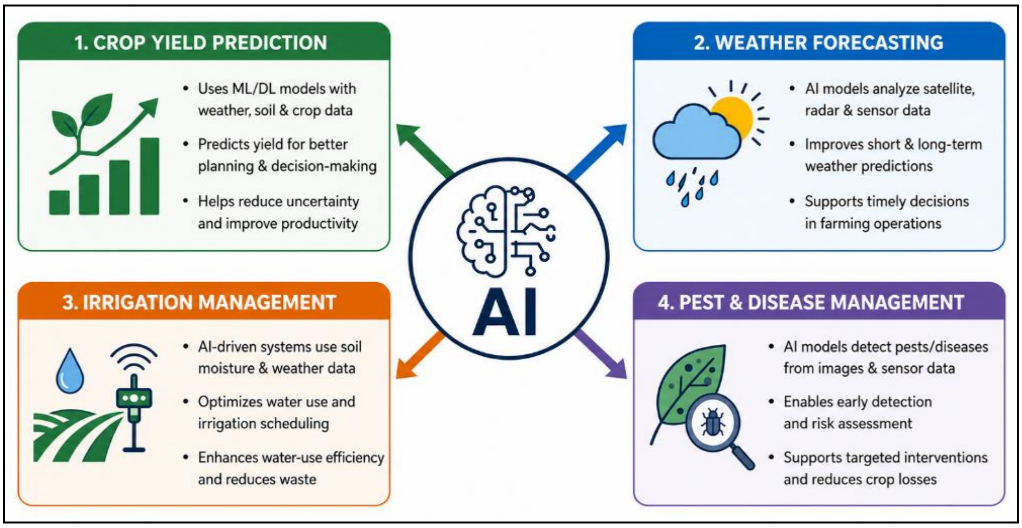

Fig 1 Integration of AI Across Four Key Themes in Climate-Smart Agriculture

The core of recent academic focus in climate-smart agriculture centers on four primary thematic pillars. As illustrated in Figure 1, the 58 papers reviewed in this study demonstrate that AI interventions are heavily concentrated on mitigating specific climate-induced vulnerabilities. Within these four domains, the literature emphasizes distinct technological applications. Research in crop yield prediction predictions frequently relies on machine learning (ML) and deep learning (DL) architectures to process historical yield metrics and soil data to minimize production uncertainty under climate stress. In weather forecasting, studies highlight how AI models surpass traditional meteorological simulations by integrating satellite observations and IoT sensor arrays for hyper-local climate predictions.

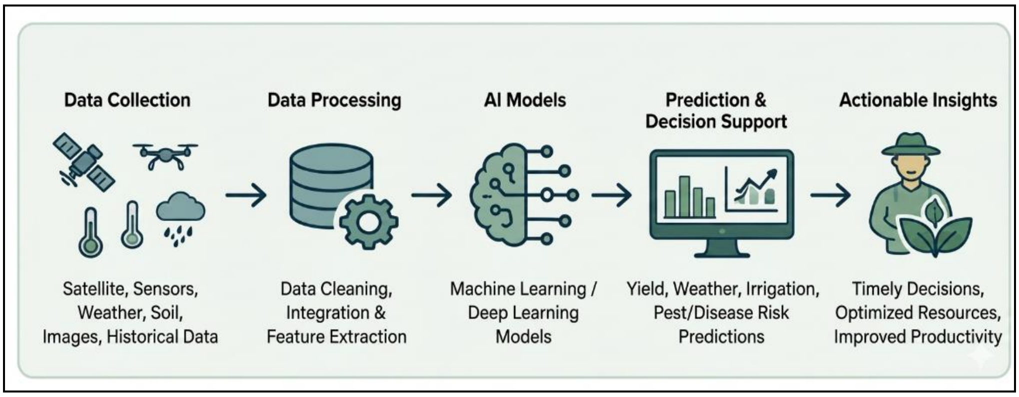

Fig 2 General Workflow of AI Applications in Climate-Smart Agricultural System

For real-time operational management, the reviewed literature focuses on irrigation systems that monitor soil moisture dynamics to automate scheduling and maximize water-use efficiency, alongside computer vision (CV) applications designed for the early detection of pests and climate-exacerbated crop diseases. While these four domains represent *what* the current research is investigating, the literature simultaneously outlines a highly standardized technical architecture detailing *how* these applications are executed. The end-to-end flow of information synthesized across these studies follows the five-stage operational pipeline depicted in Figure 2.

According to the reviewed systems, the technical pipeline initiates with multi-source data collection via remote sensing, drones, and ground sensors. Because raw field data is inherently noisy and fragmented, studies consistently highlight the necessity of a data processing stage focused on cleaning, integration, and feature extraction. This refined data is then ingested by AI models to generate predictive outputs

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for decision support systems. Ultimately, the pipeline culminates in actionable insights, translating complex algorithmic models into practical recommendations for farmers and stakeholders.

The systemic deployment of this technical workflow across the four core themes is ultimately driven by a shared goal in the literature: achieving the primary tenets of resilience and sustainability. Figure 3 synthesizes the micro and macro-level impact pathways identified across the reviewed research.

Fig 3 Key Benefits of AI-Driven Solutions in Agriculture

At the farm level, the literature documents immediate economic returns through higher productivity achieved by stabilizing food production volumes against climate shocks and enhanced resource use efficiency, which minimizes the waste of water, fertilizers, and agrochemicals. This optimization directly translates to significant operational cost reductions for both smallholder and commercial enterprises. On a broader scale, these advancements facilitate robust risk mitigation by transforming agricultural management from a reactive paradigm to a proactive, early-warning stance. By curbing over-application of chemicals and optimizing resource conservation, these coordinated pathways align modern precision farming with long-term ecological balance, establishing a concrete foundation for sustainable agriculture.

III. METHODOLOGY

This study adopted a systematic literature review approach to synthesize existing knowledge on the application of artificial intelligence in climate-smart agriculture, with emphasis on four core thematic areas: (i) AI in crop yield prediction, (ii) AI in weather and climate forecasting, (iii) AI for irrigation and water management, and (iv) AI for pest and disease detection under climate stress. The review followed a structured search, screening, and selection process to ensure transparency, reproducibility, and relevance of included studies.

➢ *Data Sources and Search Strategy*

The following keywords and search strings were applied separately: ["Artificial intelligence in agriculture", "Machine learning AND climate-smart agriculture", "AI crop yield prediction AND climate variability", "Deep learning agricultural forecasting weather prediction", "Smart irrigation systems AND IoT AND machine learning", "AI pest detection AND plant disease AND climate stress", "Precision agriculture AND artificial intelligence review", "Climate change AND agriculture AND AI applications", "Machine learning" AND "crop yield prediction", "AI" AND "weather forecasting" AND agriculture, "Smart farming" AND "IoT" AND irrigation optimization"]. These eleven (11) search strings were used in various combinations to ensure comprehensive coverage of the literature related to the study objectives.

➢ *Inclusion and Exclusion Criteria*

The study included only peer-reviewed journal articles published between 2020 and 2026. Articles were selected based on relevance to the four core thematic areas of the review. Studies that did not directly address AI applications in agriculture or were outside the climate-smart agriculture context were excluded. While conference papers, and book chapters were also considered, opinion articles, and non-peer-reviewed sources were excluded to maintain academic rigor and reliability.

➢ *Study Selection Process*

An initial total of 170 articles were identified from the database searches. These articles were screened through a multi-stage process involving title screening, abstract screening, and full-text assessment. After careful evaluation, 58 articles were retained for final inclusion in the review. The reduction in sample size was intentional to ensure that only the most relevant and high-quality studies aligned with the specific objectives of the review were included. This approach was adopted to avoid excessive inclusion of marginally related studies and to maintain a focused and value-driven synthesis of evidence.

➢ *Quality Assessment*

Each selected article was assessed based on methodological clarity, relevance to AI applications in climate-smart agriculture and publication in reputable peer-reviewed journals. Preference was given to studies employing robust methodologies such as machine learning models, deep learning frameworks, empirical field applications, and systematic reviews.

➢ *Data Analysis and Synthesis*

A thematic synthesis approach was used to analyze the selected literature. The findings were categorized into the four predefined thematic areas: crop yield prediction, weather and climate forecasting, irrigation and water management, and pest and disease detection. This allowed for structured

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comparison of methodologies, findings, and research gaps across studies. The synthesis further enabled identification of emerging trends, technological advancements, and future research directions in AI-driven climate-smart agriculture.

➢ *Ethical Considerations*

As this study is based solely on secondary data from publicly available peer-reviewed literature, no ethical approval was required. However, proper academic integrity was maintained through accurate citation and referencing of all sources.

IV. RESULTS AND DISCUSSIONS

This section is organized into four major thematic areas to provide a structured discussion of the applications of Artificial Intelligence in Climate-Smart Agriculture, namely: AI in crop yield prediction, AI in weather and climate forecasting, AI for irrigation and water management, and AI for pest and disease detection under climate stress.

➢ *AI in Crop Yield Prediction*

Accurate crop yield prediction has become increasingly important in climate-smart agriculture due to growing concerns over climate variability, food insecurity, and sustainable agricultural production. Traditional yield estimation approaches often struggle to capture the complex interactions among weather conditions, soil properties, farm management practices, and environmental stressors. Consequently, Artificial Intelligence (AI), particularly machine learning (ML), deep learning (DL), artificial neural networks (ANN), remote sensing, and explainable AI models, has emerged as a promising solution for improving prediction accuracy and supporting climate-resilient agricultural decision-making.

Several recent studies have emphasized the growing effectiveness of AI-based yield prediction systems. Shawon et al. (2024), Goel & Pandey (2024), and Jabed & Murad (2024) conducted extensive reviews and reported that machine learning and deep learning algorithms consistently outperform conventional statistical approaches in predicting crop yields under varying climatic conditions. Their findings highlighted the increasing use of random forest, support vector machines, convolutional neural networks, and recurrent neural networks in agricultural forecasting. Similarly, Gupta et al. (2025) argued that AI-driven yield prediction models improve decision-making by integrating large datasets involving weather, soil characteristics, satellite imagery, and historical crop performance.

A major point of agreement among the reviewed studies is the importance of integrating climate and soil variables into predictive models. Gadhiya (2025) developed an AI-based crop yield prediction framework using climatic and soil datasets and demonstrated that combining environmental variables significantly improves predictive performance. Likewise, Dhanke et al. (2025) emphasized that climate-based AI systems can support precision agriculture and irrigation planning by generating accurate yield forecasts under changing climatic conditions.

These findings support the broader climate-smart agriculture agenda, where predictive intelligence is increasingly used to optimize resource use and reduce climate-related production risks. Remote sensing technologies have also become central to modern crop yield prediction systems. Kavipriya & Vadivu (2024) explored the integration of remote sensing imagery with AI algorithms and found that satellite-derived vegetation indices substantially improve model accuracy.

Their findings align with those of Hu et al. (2023), who demonstrated that integrating remote sensing and explainable AI models enhances both prediction reliability and interpretability.However, Hu et al. (2023) warned against excessive dependence on “black-box” AI models, arguing that highly complex systems often reduce transparency and may lead to biased climate impact assessments if model interpretability is ignored.

While many studies report significant improvements in predictive accuracy using deep learning techniques, some researchers have highlighted concerns regarding computational complexity and data requirements. Sivaranjani & Vimal (2023) demonstrated that Artificial Neural Network (ANN)-based systems improve yield prediction accuracy substantially, particularly under variable climatic conditions. However, Hernández Hernández et al. (2025) noted that many advanced deep learning models require extensive datasets, high computational power, and technical expertise, which may limit their adoption in developing countries with limited technological capacity. Recent studies have also shown growing interest in lightweight and edge-based AI systems for real-time agricultural applications. Dhanaraj et al. (2025) proposed on-device AI systems using lightweight predictive models embedded within smart agricultural devices. Their findings suggest that decentralized AI systems can support climate-resilient farming by enabling real-time crop monitoring and yield estimation in low-resource farming environments.

This represents an important advancement toward scalable and farmer-friendly AI applications. Furthermore, Chavula et al. (2024) synthesized evidence on AI applications in climate-smart agricultural technologies and concluded that AI-driven yield prediction systems contribute significantly to climate adaptation, productivity improvement, and sustainable farm management. Their study emphasized that predictive systems are increasingly becoming part of integrated smart farming ecosystems involving IoT devices, sensors, remote sensing platforms, and climate forecasting systems. Notwithstanding the significant progress reported in the literature, several challenges continue to exist. Shawon et al. (2024), Jabed & Murad (2024), and Hernández Hernández et al. (2025) all identified issues related to data quality, model generalizability, algorithm bias, poor digital infrastructure access, and insufficient localized datasets as major barriers to large-scale implementation. Additionally, differences in climatic conditions, crop types, and farming systems across regions continue to affect the transferability of AI models. The comparative summary of selected studies on AI applications in crop yield prediction under climate-smart agriculture is presented in Table 1.

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Table 1 Comparative Summary of Recent Studies on AI Applications in Crop Yield Prediction Under Climate-Smart Agriculture

Area of Focus	AI Technique/Approach	Key Findings	Reference
Systematic review of yield prediction	ML & DL models	AI models outperform traditional statistical methods	Shawon et al. (2024)
Climate and soil-based yield prediction	AI predictive system	Climate and soil integration improves accuracy	Gadhiya (2025)
Review of ML and DL approaches	ML & DL	Deep learning improves forecasting precision	Jabed & Murad (2024)
AI applications in yield prediction	AI review	AI enhances precision agriculture decisions	Goel & Pandey (2024)
Remote sensing and yield prediction	AI + satellite imagery	Vegetation indices improve model performance	Kavipriya & Vadivu (2024)
Yield prediction accuracy	ANN	ANN improves prediction reliability	Sivaranjani & Vimal (2023)
Literature review on predictive AI models	AI predictive models	High computational demand remains a challenge	Hernández Hernández et al. (2025)
AI-based yield prediction review	ML systems	AI supports sustainable farm management	Gupta et al. (2025)
Explainable AI in yield prediction	Explainable ML	Black-box models reduce interpretability	Hu et al. (2023)
On-device AI systems	Lightweight AI models	Real-time prediction supports climate resilience	Dhanaraj et al. (2025)
AI in climate-smart agriculture	AI synthesis study	AI improves productivity and adaptation	Chavula et al. (2024)
Climate-based precision irrigation	AI-powered systems	Climate-informed AI maximizes crop yields	Dhanke et al. (2025)

Source: Author’s Compilation from Reviewed Literature (2020–2026).

The reviewed studies collectively demonstrate that AI-based crop yield prediction systems offer substantial potential for enhancing agricultural productivity, climate resilience, and precision farming.

➢ *AI in Weather and Climate Forecasting*

The importance of reliable weather and climate forecasting in climate-smart agriculture has increased significantly due to growing climate uncertainty, unpredictable rainfall, lengthy drought periods, flooding events, and fluctuations in temperature. Farmers now require timely climate information to support planting decisions, irrigation scheduling, pest management, and risk reduction. Consequently, AI has emerged as a valuable tool for improving climate prediction systems and strengthening agricultural resilience.

The reviewed studies indicate that AI technologies are significantly transforming agricultural weather forecasting through advanced data analytics, predictive modeling, and automated climate monitoring systems. Hachimi et al. (2022) reported that AI integrated with big data analytics improves weather data management and enhances precision agriculture by supporting real-time climate-based decisions.

Similarly, Dewitte et al. (2021) observed that AI-based forecasting systems have improved climate monitoring and long-term weather prediction through their ability to process large and complex environmental datasets more efficiently than traditional forecasting models. Deep learning approaches are increasingly dominating this field. Devi et al. (2024) demonstrated that recurrent neural network (RNN) algorithms effectively capture sequential weather patterns and improve forecasting accuracy within smart agricultural systems.

Their findings support the work of Rana & Lone (2025), who argued that integrated AI systems combining machine learning, satellite observations, and climate simulations provide more reliable and adaptive forecasting systems for agriculture. However, Rana & Lone (2025) cautioned that limited climate datasets, infrastructure constraints, and computational requirements remain major implementation barriers, particularly in developing countries.

Several studies further linked AI forecasting systems to broader climate-smart agriculture objectives. Kumari et al. (2025) emphasized that AI-driven forecasting technologies contribute to sustainable farming by enabling adaptive decision-making and efficient resource utilization under climate variability.

Likewise, Mandour et al. (2025) highlighted the importance of AI in strengthening food security and enhancing plant adaptation through early climate risk prediction and intelligent forecasting systems. At a broader scale, Yu et al. (2025) demonstrated that AI-supported global agricultural monitoring systems improve climate risk assessment and agricultural planning through large-scale environmental observations. Chavula et al. (2024) similarly concluded that AI applications in climate-smart agriculture enhance resilience through predictive analytics, automated monitoring, and data-driven agricultural management systems.

Though AI has played a revolutionary role in transforming modern forecasting systems, recurring concerns remain evident. Dewitte et al. (2021) and Rana & Lone (2025) both stressed that issues related to data quality, model transparency, technical expertise, and weak digital infrastructure systems continue to limit the effectiveness of AI forecasting systems in deprived agricultural regions. The comparative summary of selected studies on AI in weather and climate forecasting under climate-smart agriculture is presented in Table 2. Moreover, the excessive dependence on highly sophisticated computational systems may reduce accessibility for smallholder farmers with limited technological resources.

Table 2 Comparative Summary of Studies on AI in Weather and Climate Forecasting Under Climate-Smart Agriculture

Area of Focus	AI Technique/Approach	Key Findings	Reference
Smart weather data management	AI + big data analytics	Improved precision agriculture through real-time climate monitoring	Hachimi et al. (2022)
Weather forecasting for smart agriculture	Recurrent Neural Networks (RNN)	Enhanced forecasting accuracy for agricultural decision-making	Devi et al. (2024)
Climate-smart and sustainable agriculture	AI-driven farming systems	AI supports climate adaptation and sustainability	Kumari et al. (2025)
Integrated AI weather forecasting	ML + satellite + climate simulation	Improved reliability of agricultural forecasting systems	Rana & Lone (2025)
Climate monitoring and forecasting	AI predictive systems	AI revolutionizes weather forecasting and climate prediction	Dewitte et al. (2021)
Global agricultural monitoring	AI-supported monitoring systems	Enhanced climate risk assessment and planning	Yu et al. (2025)
AI for food security and plant adaptation	AI predictive intelligence	AI strengthens resilience and climate adaptation	Mandour et al. (2025)

Source: Author's Compilation from Reviewed Literature (2020–2026).

These reviewed studies demonstrate that AI-based weather and climate forecasting systems are becoming essential components of climate-smart agriculture. Through improved predictive accuracy, climate monitoring, and adaptive decision-making, these technologies contribute significantly to sustainable agricultural production and climate resilience.

- *AI for Irrigation and Water Management*

Water scarcity remains one of the most serious threats to sustainable agricultural production, particularly in regions experiencing increasing climate variability, prolonged droughts, and erratic rainfall patterns. As pressure on freshwater resources intensifies, the agricultural sector is increasingly shifting toward intelligent irrigation systems capable of optimizing water use efficiency while maintaining crop productivity. Across the reviewed literature, Artificial Intelligence (AI), the Internet of Things (IoT), predictive analytics, simulation models, and automated sensor technologies are consistently identified as major innovations transforming irrigation and agricultural water management within climate-smart agriculture frameworks.

A recurring theme across the studies is the integration of AI with IoT- enabled monitoring systems. Patidar et al. (2025), Soy & Salwadkar (2024), and Benhmad et al. (2024) all emphasized that combining AI algorithms with soil moisture sensors, weather stations, and automated irrigation controllers significantly improves irrigation precision and reduces unnecessary water application. These studies collectively suggest that real-time data acquisition and automated decision-making enhance both water conservation and crop performance. Similarly, Bayar et al. (2025) introduced the concept of Artificial Intelligence of Things (AIoT), where interconnected smart systems simultaneously manage irrigation, nutrient application, and pest control within precision agriculture ecosystems.

Several authors focused specifically on climate resilience and sustainability dimensions of AI-powered irrigation systems. Naqvi et al. (2025), and AbdelRahman (2026) argued that climate-resilient water management systems supported by AI can substantially strengthen agricultural adaptation to drought and water stress. The findings reveal that AI-driven irrigation scheduling improves water allocation efficiency by continuously adjusting irrigation based on soil conditions, crop water requirements, and anticipated climatic variations. Dhanke et al. (2025) similarly demonstrated that climate-based AI-powered precision irrigation frameworks maximize crop yields while minimizing water wastage, making them highly suitable for climate-smart farming systems.

The reviewed studies further reveal growing interest in simulation-based and predictive irrigation management approaches. Dewedar et al. (2023) observed that simulation models combined with AI significantly improved irrigation management under dry environmental conditions by predicting water demand more accurately than conventional methods. Likewise, Alvim et al. (2022), through a systematic review, concluded that AI applications in irrigation management consistently improved water productivity, irrigation timing, and resource efficiency across different agricultural environments.

Another emerging direction within the literature involves the development of affordable and energy-efficient smart irrigation technologies. Akanbi et al. (2025) explored AI-powered solar irrigation systems and found that integrating renewable energy with AI-based water management systems offers substantial potential for sustainable agricultural intensification, particularly in water-stressed rural regions. Ali et al. (2025) also emphasized that smart irrigation technologies enhance sustainable agriculture through efficient water utilization, lower operational costs, and reduced environmental degradation.

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However, several studies have also identified notable implementation challenges. Ahmed et al. (2023), Mishra et al. (2025), and Trace et al. (2023) highlighted concerns relating to high installation costs, infrastructure limitations, poor internet connectivity, limited farmer technical capacity, and inadequate access to digital technologies in many developing countries. The comparative summary of selected studies on AI for irrigation and water management under climate-smart agriculture is presented in Table 3.

Table 3 Comparative Summary of Studies on AI for Irrigation and Water Management Under Climate-Smart Agriculture

Area of Focus	AI Technique/Approach	Key Findings	Reference
Smart water systems	AI + IoT	Improved irrigation precision and water efficiency	Patidar et al. (2025)
AIoT in precision agriculture	AIoT systems	Integrated irrigation, nutrient, and pest management	Bayar et al. (2025)
Smart irrigation optimization	AI irrigation systems	Optimized water allocation and crop performance	Al khatib & Alshaib (2025)
Climate-resilient water management	Integrated AI systems	Enhanced sustainable soil-water-crop management	AbdelRahman (2026)
Precision irrigation frameworks	Climate-based AI	Maximized crop yields with reduced water wastage	Dhanke et al. (2025)
Climate-resilient water management	IoT + AI	Improved adaptive irrigation scheduling	Naqvi et al. (2025)
Smart irrigation technologies	AI water-use systems	Increased water use efficiency and sustainability	Ali et al. (2025)
Smart irrigation under climate change	AI irrigation management	Improved water productivity in drylands	Ahmed et al. (2023)
Irrigation management review	AI systematic review	AI improves irrigation timing and efficiency	Alvim et al. (2022)
AI-based irrigation technologies	Smart irrigation systems	Enhanced automated water management	Trace et al. (2023)
AI-driven water systems	Intelligent irrigation systems	Improved precision water management	Mishra et al. (2025)
IoT-based smart irrigation	IoT + AI	Efficient water resource management	Soy & Salwadkar (2024)
Irrigation simulation models	AI + simulation models	Better irrigation prediction in dry environments	Dewedar et al. (2023)
Integrated smart irrigation systems	IoT + AI integration	Real-time irrigation control and monitoring	Benhmad et al. (2024)
Solar irrigation systems	AI-powered solar irrigation	Sustainable and energy-efficient water management	Akanbi et al. (2025)

Source: Author’s Compilation from Reviewed Literature (2020–2026).

The AI-based irrigation systems often require uninterrupted data flow and complex modelling frameworks, which can constrain their applicability in smallholder farming contexts. Collectively, the literature highlights the growing role of AI in irrigation and water management as a core element of climate-smart agriculture, enhancing water use efficiency, climate resilience, and sustainable production outcomes.

➢ *AI for Pest and Disease Detection Under Climate Stress*

Climate change has accelerated the emergence, spread, and intensity of crop pests and plant diseases, creating serious threats to agricultural productivity and food security. Rising temperatures, shifting rainfall patterns, and increased humidity have altered pest behavior and disease dynamics across many farming systems. As a result, recent studies increasingly recognize AI as a critical tool for rapid pest surveillance, disease diagnosis, and climate-responsive crop protection.

The reviewed studies reveal growing adoption of machine learning, deep learning, remote sensing, and IoT-based systems for pest and disease management. Ali et al. (2024) noted that AI technologies improve early detection of climate-induced plant pathogens through predictive analytics and automated diagnosis systems. Similarly, Delfani et al. (2024) demonstrated that integrating IoT, machine learning, and AI significantly enhances disease forecasting accuracy under changing climatic conditions. Several studies emphasized the role of deep learning and remote sensing in improving detection efficiency. Wu et al. (2025) reported that deep learning-based AI systems provide high accuracy in identifying crop diseases and insect infestations from field images and sensor data. Sharada et al. (2025) further showed that AI-driven remote sensing platforms strengthen global food security by enabling real-time pest monitoring and precision intervention strategies.

In addition, Bukhari et al. (2025) and Biswal et al. (2025) highlighted that AI-supported forecasting models can predict future pest outbreaks under climate stress, thereby

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supporting proactive farm management. However, Anand & Sandhu (2024) cautioned that limited datasets, technological costs, and insufficient farmer training continue to hinder widespread adoption in many developing agricultural systems.

The reviewed literature indicates that AI-driven pest and disease detection systems are increasingly strengthening crop protection, improving surveillance, reducing losses, and supporting climate-resilient agricultural management under changing environmental conditions. Table 4 shows an in-depth comparison of the reviewed literatures.

Table 4 Comparative Summary of Studies on AI for Pest and Disease Detection Under Climate Stress

Area of Focus	AI Technique/Approach	Key Findings	Reference
Climate-induced plant pathogens	AI predictive systems	Improved early pathogen detection	Ali et al. (2024)
Insect pest dynamics	AI forecasting models	Better prediction of pest outbreaks	Bukhari et al. (2025)
Disease forecasting	IoT + ML + AI	Enhanced forecasting under climate change	Delfani et al. (2024)
Plant disease forewarning	AI forecasting models	Improved proactive disease management	Biswal et al. (2025)
Pest and disease management	AI applications review	AI strengthens agricultural protection systems	Li & Wang (2024)
Deep learning in pest detection	Deep learning AI	High detection accuracy from image datasets	Wu et al. (2025)
Biotic stress management	AI technologies	AI improves crop stress management	Anand & Sandhu (2024)
Remote sensing pest management	AI + remote sensing	Real-time pest monitoring supports food security	Sharada et al. (2025)
ML for crop pest detection	Machine learning	Improved crop disease identification	Amulothu et al. (2024)

Source: Author’s compilation from reviewed literature (2020–2026).

- ➢ *Challenges Limiting the Adoption and Effectiveness of AI in Climate-Smart Agriculture*

Despite the growing importance of AI in climate-smart agriculture, several challenges continue to limit its effective implementation across agricultural systems. One of the major constraints identified in the literature is the lack of reliable and high-quality agricultural data, particularly in developing countries. Many AI models require large datasets for accurate prediction and analysis; however, inadequate digital infrastructure, poor record-keeping systems, and limited access to climate and farm-level data reduce the effectiveness of AI applications in areas such as crop yield prediction, weather forecasting, irrigation management, and pest detection.

Another major challenge is the high cost associated with AI technologies and smart farming equipment. The installation and maintenance of AI-powered systems, sensors, drones, remote sensing technologies, and IoT devices often require significant financial investment, making them difficult to afford for many smallholder farmers. In addition, operational costs related to internet connectivity, software maintenance, and technical support further limit adoption, especially in low-income agricultural regions. Limited farmer awareness and adoption also remain critical barriers.

Although AI technologies offer substantial benefits for climate-smart agriculture, many farmers lack the technical knowledge and digital literacy required to effectively utilize these systems. Resistance to new technologies, inadequate training opportunities, and limited extension support continue to slow the integration of AI into routine farming practices. Furthermore, climate uncertainty itself presents a major challenge for AI-based agricultural systems. Rapidly changing weather conditions, unpredictable rainfall patterns, extreme climatic events, and regional environmental variability can reduce the accuracy and reliability of predictive AI models. Since many AI systems depend heavily on historical datasets, unexpected climate shifts may affect forecasting performance and reduce decision-making efficiency.

These challenges collectively indicate that while AI offers considerable potential for strengthening climate-smart agriculture, significant technological, economic, infrastructural, and environmental barriers still need to be addressed for effective and inclusive adoption.

- ➢ *Future Prospects and Strategic Directions for AI in Climate-Smart Agriculture*

The future of AI in climate-smart agriculture will largely depend on the development of localized, accessible, and farmer-centered technologies. One important direction is the increased use of local agricultural and climate data to develop region-specific AI models, particularly for African farming systems where environmental conditions, farming practices, and data availability differ significantly from developed regions.

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Such localized models are expected to improve prediction accuracy and decision-making reliability. Another key area involves the integration of AI technologies with mobile applications and digital advisory platforms. Mobile-based AI systems can provide farmers with real-time information on weather conditions, irrigation scheduling, pest outbreaks, and crop management practices, thereby improving accessibility among smallholder farmers. In addition, stronger policy support for digital agriculture will be essential for scaling AI adoption. Government investment in rural digital infrastructure, farmer training, research collaboration, and affordable smart farming technologies can significantly enhance the effective implementation of AI-driven climate-smart agricultural systems.

V. CONCLUSIONS

This review has examined the expanding role of Artificial Intelligence (AI) in advancing Climate-Smart Agriculture (CSA) through four key domains: crop yield prediction, weather and climate forecasting, irrigation and water management, and pest and disease detection under climate stress. The synthesis of recent literature demonstrates that AI technologies, including machine learning, deep learning, remote sensing, IoT, and data-driven predictive systems, are fundamentally reshaping agricultural decision-making and improving system-level resilience to climate variability. Across the reviewed studies, AI consistently enhances prediction accuracy, optimizes resource use, and strengthens early warning systems, thereby contributing to more efficient and sustainable agricultural production systems.

Despite these advancements, the review also highlights persistent structural and operational challenges, particularly in developing regions. These include limited access to high-quality data, high implementation costs, inadequate digital infrastructure, low farmer adoption rates, and uncertainties associated with rapidly changing climatic conditions. These constraints continue to hinder the full-scale deployment and equitable benefits of AI technologies in agriculture.

Nevertheless, the evidence indicates strong potential for AI to become a central pillar of future agricultural transformation when supported by appropriate enabling environments. The integration of localized datasets, mobile-based advisory systems, and supportive agricultural policies is critical for ensuring inclusivity and scalability. Strengthening collaborations among researchers, policymakers, technology developers, and farming communities will further accelerate the responsible deployment of AI-driven solutions.

Overall, AI represents a powerful enabler of climate-smart agriculture, offering transformative opportunities to improve productivity, resilience, and sustainability. However, its long-term success will depend on addressing existing barriers and ensuring that technological advancements are aligned with the practical realities of diverse farming systems.

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