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Review Article

Artificial intelligence for climate-smart agriculture: Enhancing food security and plant adaptation

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Abstract

Global climate change is an accelerating, multifaceted threat to food security and agricultural stability, requiring innovative solutions that surpass the efficacy of conventional breeding and farming practices. This review synthesizes recent advances in AI-driven approaches for climate-smart agriculture, emphasizing their unique and transformative potential in accelerating climate adaptation, optimizing resource use. We examine AI's multifaceted applications across four critical domains: high-throughput precision agriculture, accelerated genetic engineering, advanced crop yield modeling, and granular climate and pest forecasting. Specifically, we detail how AI-driven tools-including IoT sensor networks, computer vision models for phenotype screening, and deep learning algorithms-enable real-time, plant-specific nutrient and water management. Furthermore, the review illustrates how AI has the potential to markedly support and accelerate the discovery and validation of stress-resilience genes. Critically, we address the significant ethical and structural challenges impeding AI adoption, including data heterogeneity and scarcity, the potential for algorithmic bias to widen existing resource gaps, and barriers to equitable access for smallholder farmers. A key achievement is the synthesis of AI's utility in predicting crop performance under future environmental scenarios and providing actionable, site-specific recommendations to farmers and policymakers. We conclude by advocating for essential policy and governance pathways, emphasizing the necessity of transparent international data-sharing frameworks and inclusive technology transfer to ensure that AI's benefits are harnessed effectively and equitably, thus strengthening global agricultural resilience against future climate shocks.

Keywords: artificial intelligence; climate change; crop monitoring; food security; plant breeding; sustainable agriculture

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Introduction

The world faces a critical climate emergency, necessitating urgent actions to mitigate its impacts and adapt to ongoing and future changes (Hoque *et al.*, 2022). Climate change refers to substantial and enduring alterations in the Earth's climate, primarily characterized by rising temperatures largely driven by human activities such as the burning of fossil fuels (Wuebbles and Jain, 2001).

Elevating global temperatures, erratic precipitation patterns, and increased frequency of extreme weather events such as drought and floods pose a significant threat to global food production (Foley *et al.*, 2011; Lobell *et al.*, 2011). According to World Meteorological Organization (WMO, 2025), Annual global mean temperature anomalies (relative to an 1850 - 1900 pre-industrial baseline) demonstrate a clear upward trajectory from 1850 to 2024. In the mid-19th century, anomalies fluctuated modestly, often remaining close to zero, but over time a gradual warming trend emerged. During the 20th century, warming intensified, interrupted occasionally by short-term fluctuations, but from the 1970s onward the increase became more pronounced. In recent years, the anomaly has exceeded 1 °C, reaching a record ~1.53 °C in 2024 (World Meteorological Organization, Dashboard "Global mean temperature 1850 - 2024"). This sustained rise highlights the accelerating impact of human-induced climate change and underscores the urgency of mitigation and adaptation measures (Figure 1A). A more rapid pace of warming, around 0.2 °C per decade, is projected for the next two decades, with substantially larger trends anticipated for cultivated land areas (Chen *et al.*, 2018).

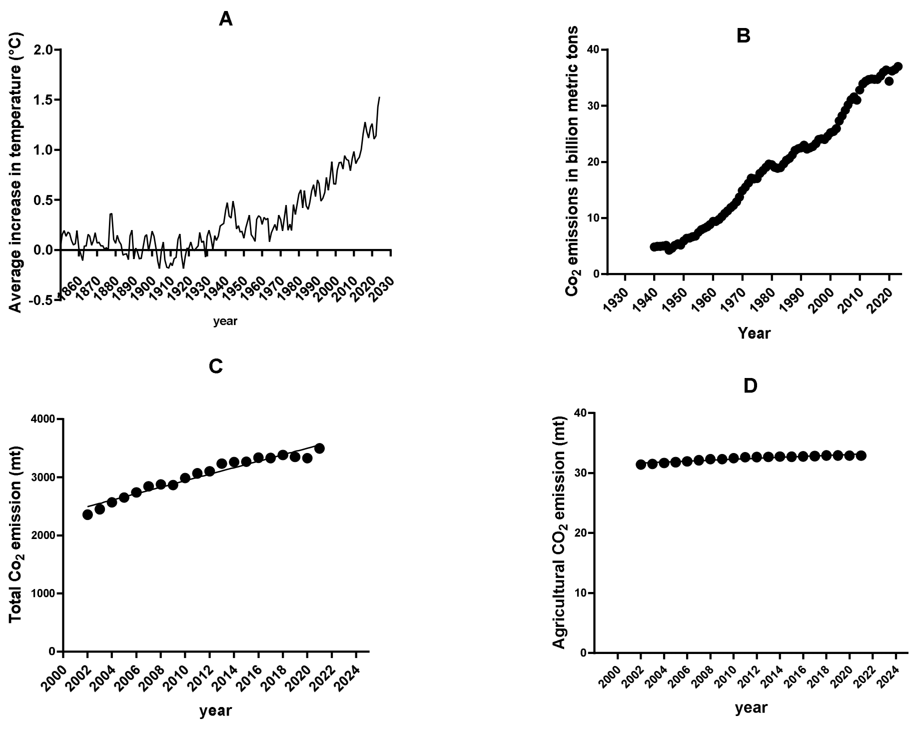

Figure 1. (A) Average global temperatures by decade from 1900 to 2020, based on historical data from WMO 2025. (B) Changes in world's Co$_2$ emissions across the last 9 decades, (Statista, 2024, *https://www.statista.com/statistics/276629/global-co2-emissions/*)

Data extracted from worldwide; global carbon project (Jones *et al.*, 2023); Statista; 1930 to 2024; *Projection. (C) Total CO_2 emissions (Mt) show a steady increase over the study period, with a linear trend indicating continued growth. (D) Agricultural CO_2 emissions (Mt) also exhibit an upward trajectory, though at a smaller scale compared to total emissions, (FAO, 2022, *https://www.fao.org/faostat/en/#data/GPP*)

For decades, scientists have cautioned about the looming dangers of climate change, fueled by rising greenhouse gas emissions and widespread ecosystem disruptions. As early as 1979, experts from 50 nations gathered at the First World Climate Conference in Geneva, concluding that the early warning signs of climate change demanded urgent measures to avoid human-induced alterations that could harm global well-being. In fact, both independent academic researchers and fossil fuel companies had accurately forecast global warming nearly half a century ago - well before its effects became evident (Supran *et al.*, 2023). Yet, despite these longstanding alerts, humanity remains off course. Fossil fuel emissions have reached record highs, July 2024 marked the three hottest days ever recorded (Guterres, 2024).

Greenhouse gases (GHGs), such as CO_2, retain heat within Earth's atmosphere, intensifying the greenhouse effect. Among human-generated GHGs, CO_2 is the primary driver of global warming and climate change (Bajoria *et al.*, 2024). It is produced by both natural processes as well as human activities, particularly the burning of fossil fuels, deforestation, and industrial operations (Friedlingstein *et al.*, 2020). Elevated atmospheric CO_2 concentrations enhance heat retention, driving global temperature increases. These shifts disrupt weather patterns, accelerate polar ice melt, raise sea levels, and intensify both the frequency and severity of extreme weather events. With a Global Warming Potential (GWP) of 1, CO_2 serves as the benchmark for evaluating the impacts of other greenhouse gases. Globally, CO_2 levels have reached unprecedented highs, showing a pronounced rise since the early 21st century (Figure 1B). According to FAO statistics (2022), total CO_2 emissions reached 3,496.94 million tons (mt), with 32.40 mt originating from agricultural production. Over the past two decades, overall CO_2 emissions have increased by approximately 42.68% (Figure 1C), while agricultural emissions have risen by 2.75% (Figure 1D). In contrast, some regions-such as southern Europe-and certain crops-like winter wheat-may benefit from higher atmospheric CO_2 and warmer temperatures, potentially extending the growing season in temperate and cooler climates.

The effects of higher temperatures, reduced water, and increased CO2 on crop yields vary depending on the specific crop, its variety, cultivation practices, and geographical location (Tausz-Posch *et al.*, 2013; Tipping *et al.*, 2017). Therefore, identifying the specific crops and regions most affected by recent trends will enhance the ability to assess and evaluate current adaptation strategies.

As climate change accelerates and traditional crop breeding techniques along with conventional farming practices fall short in coping with these swift shifts, it becomes essential for communities, businesses, and governments to take proactive measures, seeking innovative strategies to adapt and protect against its impacts (Tester and Langridge, 2010; Fedoroff, 2015). One of the most promising and impactful approaches is the application of artificial intelligence (AI), in which machines have the ability to "learn from data, adapt to new information, and perform tasks comparable to human capabilities (Sharifi and Khavarian-Garmsir, 2023). AI has shown remarkable potential in tackling the complex challenges associated with climate change (Taddeo *et al.*, 2021). These technologies enable researchers to better understand intricate plant - environment interactions, speed up the development of climate-resilient crops, and support farmers in making timely, data-driven decisions to adjust their practices in response to shifting conditions (Harfouche *et al.*, 2019). This review explores AI-driven strategies in agriculture, with a particular emphasis on their role in improving plant adaptation to climate change.

Despite a rapidly growing body of literature on AI applications in agriculture, a clear synthesis focusing specifically on plant adaptation to climate change remains limited. Existing reviews often examine AI in agriculture broadly without integrating genetic engineering, precision farming, climate modeling, and scenario planning into a unified framework. Therefore, this review aims to bridge this gap by providing a comprehensive analysis of how AI technologies contribute to climate-smart agriculture, with particular emphasis on plant adaptation mechanisms, modelling capacities, and future policy directions.

Overview of Plant Adaptation to Climate Change

Plants supply more than 80% of the food consumed by humans and serve as the primary feed source for livestock. Global warming and heatwaves directly threaten food security. To cope with climate change, plants employ diverse strategies, such as physiological adjustments, phenotypic plasticity, and genetic adaptation (Ghalambor *et al.*, 2007), (Figure 2). Natural selection is crucial in shaping traits that enable plants to survive under changing environmental conditions (Hoffmann and Sgrò, 2011). However, the current, unprecedented rate of climate change raises concerns that plants may be unable to adapt quickly enough without human intervention (Hawkins and Sutton, 2016). Additionally, climate change is projected to influence the distribution and aggressiveness of fungal pathogens, herbivores, and other pests, as well as alter plant responses to these threats.

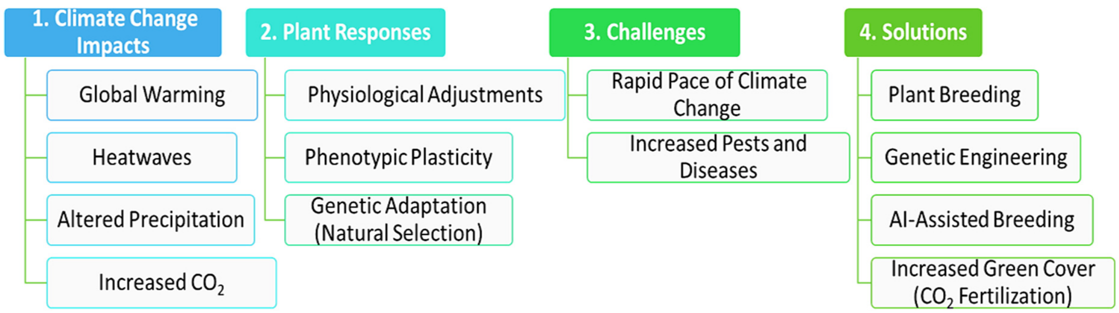

Figure 2. Framework illustrating the cascade from climate change impacts to plant responses, associated challenges, and potential solutions

Satellite observations show that the Earth has become significantly greener in the past three decades. Much of this increase in leaf area-particularly in trees-is attributed to rising atmospheric CO_2 concentrations and nitrogen deposition (Tipping *et al.*, 2017).

Traditionally, crop resilience has been improved through breeding programs and genetic engineering (Razzaq *et al.*, 2021). More recently, artificial intelligence (AI) has begun to accelerate these approaches, enhancing the capacity of plants to withstand climate-related stressors (Harfouche *et al.*, 2019).

The Role of AI in Climate-Smart Agriculture (CSA)

Climate-smart agriculture (CSA) is an integrated approach that aims to sustainably increase agriculture productivity, enhances resilience to climate change, and mitigates greenhouse gas emissions. This three-pronged approach recognizes that food security and development are the overarching goals of CSA (Palombi and Sessa, 2013; Lipper *et al.*, 2014). To achieve these goals, CSA focuses on: (a) enhancing agricultural productivity through sustainable practices to ensure food security for a growing population and build resilience to climate variability; (b) enhancing adaptation and resilience by adjusting agricultural practices to withstand climate change impacts, such as extreme weather events and gradual shifts in climate patterns; and (c) mitigating greenhouse gas emissions from agricultural activities by promoting carbon sequestration, improving energy and water use efficiency, and adopting low-emission farming practices.

CSA encompasses a range of practices, including improved soil and water management (e.g., conservation tillage, efficient irrigation), agroforestry, diversified cropping systems, and access to climate information services (Lipper *et al.*, 2014). Key examples of CSA in practice include the utilization of drought-resistant crop varieties to maintain productivity under changing climatic conditions and the implementation of improved livestock management practices to enhance efficiency and reduce environmental impact. Additionally, AI plays a significant role in predictive modelling allowing farmers to anticipate how crops will respond to future climate conditions, enabling proactive adaptation strategies (Fuentes-Peñailillo *et al.*, 2024). Furthermore, the integration of AI technologies, such as machine learning and neural networks, is revolutionizing CSA by enabling data-driven decision-making, predictive modelling of crop responses to future climate conditions, and the optimization of farming practices for both productivity and environmental sustainability (Rojas-Downing *et al.*, 2017; Fuentes-Peñailillo *et al.*, 2024; Zheng *et al.*, 2024).CSA integrates several core components. Soil and water management is a key pillar, encompassing techniques such as conservation tillage, water harvesting, and efficient irrigation systems to conserve resources and bolster resilience against droughts and floods (Lipper *et al.*, 2014). Furthermore, diversified cropping systems, which include crop rotation, intercropping, and the use of improved seed varieties, are crucial for increasing resistance to pests, diseases, and extreme weather conditions. Finally, climate information services are essential, providing farmers with data and tools to anticipate weather changes and make informed decisions regarding their planting, harvesting, and resource management (Figure 3).

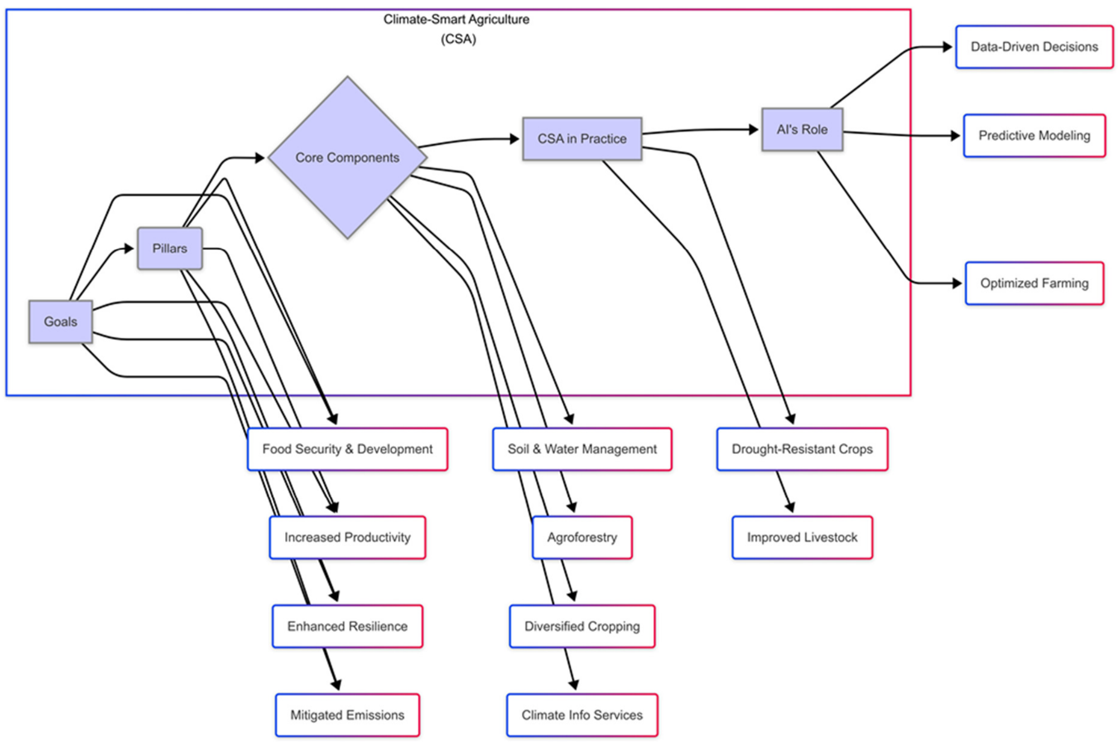

Figure 3. Conceptual framework linking Climate-Smart Agriculture (CSA) goals, pillars, and core components to practical applications, and highlighting the potential roles of Artificial Intelligence (AI)

The Role of AI in Revolutionizing Plant Genetic Engineering

A highly promising avenue for applying AI in enhancing plant adaptation to climate change is through genetic engineering. Unlike conventional techniques, AI systems can derive deeper and less biased insights from high-throughput sequencing and imaging datasets (Yang *et al.*, 2020). Specifically, Machine Learning (ML) models are applied to analyze omics data (e.g., genomics, transcriptomics, metabolomics) to identify quantitative trait loci (QTLs) and candidate genes linked to abiotic stress tolerance (e.g., heat, drought). For example, the large language model (LLM) - powered ChatGPT-a sophisticated chatbot capable of generating text and images from natural language prompts, has contributed to sparking thought-provoking questions in plant science (Agathokleous *et al.*, 2024). This capability has been instrumental in addressing knowledge gaps identified by plant researchers in projects such as the One Hundred Important Questions Facing Plant Science (Armstrong *et al.*, 2023). AI can markedly speeds up the discovery of genes associated with critical traits, including drought tolerance, heat resistance, and pest resilience. By processing extensive genomic datasets, AI algorithms can detect intricate patterns and correlations that may be difficult for human experts to recognize. When combined with tools like CRISPR (Clustered Regularly Interspaced Short Palindromic Repeats), AI-powered models enable precise genetic modifications to develop crops better adapted to climate-related stressors. Moreover, AI-driven genetic research is transforming the creation of climate-resilient plant varieties by predicting how crops will respond under future environmental scenarios, thereby supporting proactive adaptation strategies (Zscheischler *et al.*, 2020). However, applying AI to plant genetic engineering is not without challenges, including the risk of model bias, limited availability of high-quality annotated genomic datasets, and uncertainties related to predicting off-target effects in gene editing.

AI in Precision Agriculture for Climate Adaptation

Artificial intelligence is transforming agriculture through precision farming, a method that uses advanced technologies to monitor and meet the specific needs of individual plants within a field. The integration of adaptive AI into modern farming represents a fundamental shift in how crops cultivated, harvested, and managed. This evolution-from traditional, reactive methods based on historical data to proactive, data-driven strategies powered by autonomous algorithms and real-time analytics-is essential for meeting the rising global food demand while addressing sustainability challenges.

According to (Saravanan *et al.*, 2023), cloud computing plays a central role in agricultural innovation by enabling the integration of Internet of Things (IoT) algorithms, Ensemble Learning, and Explainable AI (XAI) within a Reinforcement Learning framework. By deploying AI-enabled sensors, drones, and autonomous machinery, farmers can continuously monitor crop health, soil moisture, and environmental conditions. These real-time insights facilitate precise resource management, including optimized irrigation and fertilizer application-a critical capability under climate-driven water scarcity. AI-powered precision agriculture not only boosts crop productivity, but also reduces the environmental impact of farming by minimizing waste and optimizing resource utilization (Pierre *et al.*, 2023). This approach supports the transition toward sustainable farming systems by lowering the ecological footprint of agricultural operations (Figure 4)

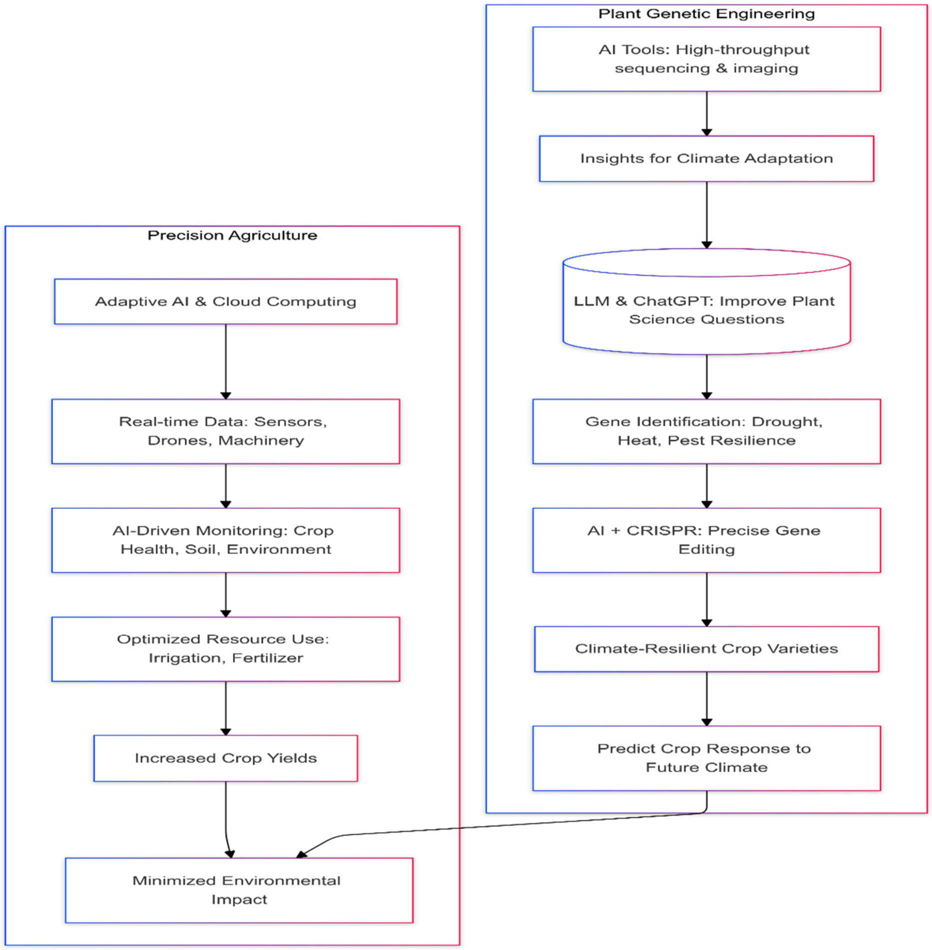

Figure 4. The Role of AI in plant genetic engineering and precision agriculture for climate change adaptation

Key Contributions of AI in Precision Agriculture

Artificial intelligence (AI) is transforming precision agriculture by providing real-time, data-driven insights into crop health, growth, and potential threats. AI-enabled sensors and cameras-mounted on drones or deployed in field-based systems, continuously capture information on parameters such as plant growth stages, the presence of pest or disease, and overall crop health. For example, Mandour *et al.* (2023) demonstrated the effective use of wireless sensor networks that integrated Omega probes, Quantum sensors, and the Hortimax system to remotely track critical environmental metrics, including temperature, relative humidity, and light intensity. Such wireless systems are particularly advantageous in areas where wired infrastructure is impractical. AI algorithms then process this incoming data in real time, detecting patterns and anomalies that may signal emerging issues, which allows farmers to act promptly, optimize resource allocation, and improve crop productivity (Muhie, 2022). In addition to real-time monitoring, AI uses historical datasets, satellite imagery, and meteorological data to forecast crop yields and assess risks related to climate variability, soil moisture deficits, and pest outbreaks (Chlingaryan *et al.*, 2018). By leveraging these predictive models, farmers can proactively manage potential threats, thereby reducing yield losses.

A major application of AI lies in irrigation optimization, a critical response to climate-driven water scarcity. By integrating soil moisture data, localized weather forecasts, and crop-specific water requirements, AI-driven systems ensure precise water delivery. This approach minimizes waste and promotes sustainable water use (Munir *et al.*, 2018). The rise of AI-powered autonomous machinery has also significantly enhanced farming efficiency. These machines can perform tasks like planting, harvesting, and weeding with high accuracy. They can also analyze soil quality, detect pests, and apply treatments selectively. This targeted approach reduces the use of broad-spectrum pesticides and fertilizers which in turn lowers costs, minimizing environmental harm, and improves operational efficiency (Kumar *et al.*, 2024b).

Furthermore, the integration of AI with advanced genetic engineering tools like CRISPR-Cas9 is accelerating the creation of climate-resilient, pest-resistant, and disease-tolerant crop varieties. Machine learning algorithms can analyze vast genetic datasets to pinpoint desirable traits, thereby streamlining the breeding of cultivars optimized for challenging environmental conditions (Chen *et al.*, 2024). Despite these benefits, AI-enabled precision agriculture faces several challenges. Models may suffer from overfitting when trained on limited or unrepresentative datasets, leading to poor real-world performance. Hardware costs, including sensors, drones, and computational infrastructure, remain prohibitive for many farmers. Additionally, unreliable or noisy data streams-such as inconsistent internet connectivity or sensor failure-can compromise model accuracy and decision-making reliability.

Finally, AI-especially when combined with machine learning and computer vision-is proving indispensable in the early detection of pest and diseases. By analyzing high-resolution imagery, these systems can detect subtle, early-stage signs of plant health problems, enabling rapid intervention. Such image recognition capabilities facilitate real-time scanning and diagnosis in the field, minimizing crop losses and reducing the need for extensive chemical applications (Pantazi *et al.*, 2019).

AI-Powered Simulation and Modelling for Future Scenarios

AI is uniquely positioned to simulate complex agro-ecosystems and forecast a variety of future scenarios, making it an essential tool for agricultural adaptation to climate change. By integrating diverse datasets-including satellite imagery, historical climate records, soil moisture, solar radiation, CO_2 concentrations, and genomic crop data-AI models can project how crops will perform under evolving environmental conditions (Miranda *et al.*, 2024). Although AI models excel at pattern recognition, they often struggle with unprecedented or rare climate events-such as extreme floods or heatwaves-because such events are underrepresented in training datasets.

Recently developed physics-informed neural networks marry physical crop-growth laws with AI's predictive capabilities to achieve both accuracy and interpretability. For example, hybrid models that combine crop simulation with AI have achieved an R^2 of up to 0.77, outperforming traditional black-box models and offering explainable outputs grounded in physical reasoning (Miranda *et al.*, 2024).

Another effective hybrid approach involves coupling mechanistic crop models with machine learning. In the US Corn Belt, such models reduced prediction error (RMSE) by 7-20%, particularly by leveraging critical variables like soil moisture and drought stress (Shahhosseini *et al.*, 2021). Spatial extensions have enabled fine-resolution yield simulations, achieving agreement indices of up to 0.95, even under varying nitrogen inputs and wheat cultivars (Kheir *et al.*, 2023)

Furthermore, Bayesian hierarchical models offer probabilistic crop yield predictions that account for uncertainties in climate models and parameters, providing calibrated scenarios vital for informed policymaking (Li *et al.*, 2025).

These advanced AI-enabled forecasting tools empower stakeholders at all levels: Policymakers can craft resilient agricultural policies grounded in site-specific risk assessments, Researchers can prioritize the development of climate-adaptive crop varieties, and farmers can fine-tune planting times and optimize irrigation and input allocation, thereby boosting both productivity and resilience.

The Role of AI in Climate Change Simulations

AI in climate data analysis

The rapid growth of climate data-from satellite imagery and meteorological stations to remote sensing networks-has surpassed the capabilities of traditional statistical methods. These methods struggle to efficiently process such vast volumes and extract meaningful patterns. AI, particularly machine learning (ML) and deep learning (DL), is uniquely suited for this challenge, offering the computational power needed to decipher complex, multi-dimensional climate data and reveal nuanced relationships (Pichler and Hartig, 2023) (Figure 5).

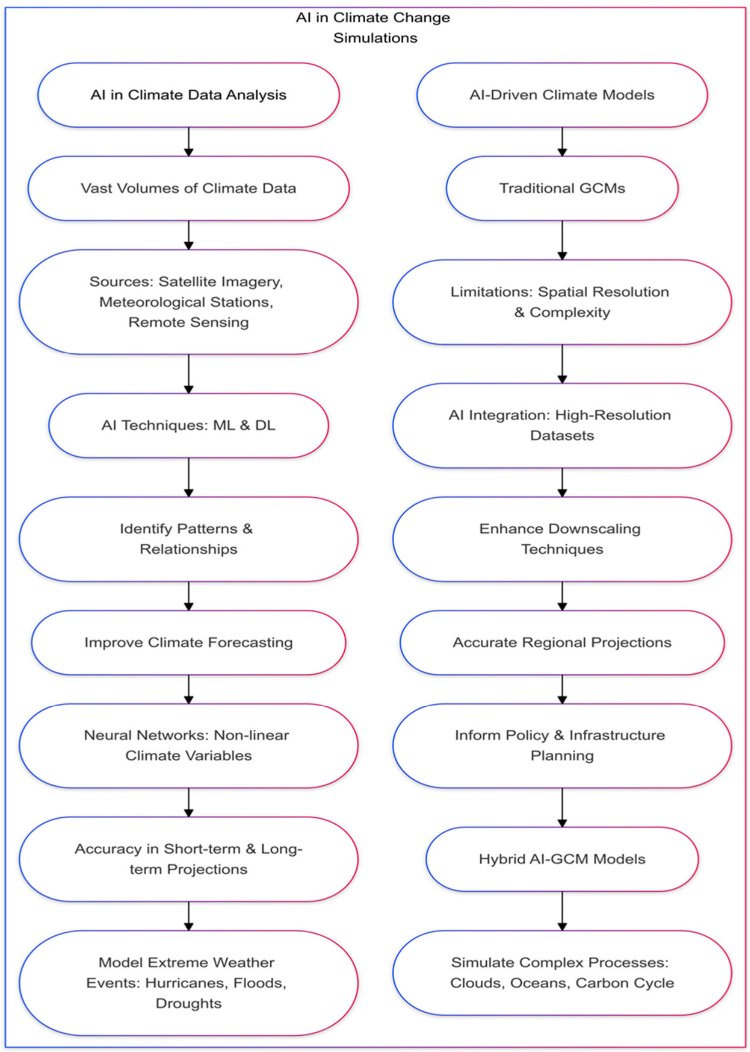

Figure 5. The role of AI in advancing climate change simulations and analysis or how AI is transforming climate science: from data analysis to enhanced modelling

One high-impact application of AI in climate science is weather forecasting. State-of-the-art models like DeepMind's GraphCast - a Graph Neural Network (GNN)-based system - have demonstrated exceptional accuracy, outperforming European Centre for Medium-Range Weather Forecasts (ECMWF) high-resolution forecasts in over 90% of test variables and lead times. Similarly, Huawei's Pangu-Weather, a 3D deep learning model employing transformer architectures, has surpassed conventional numerical weather prediction (NWP) systems in both accuracy and computational efficiency.

These AI systems not only accelerate forecasts (GraphCast can deliver 10-day global predictions in under a minute) but also significantly reduce the computational burden. These advancements are already being deployed operationally. For instance, Taiwan's Central Weather Administration has used AI models to predict typhoon tracks with approximately 20% higher accuracy over a three-day window compared to traditional methods. ECMWF has also launched an AI-based forecasting system that can predict severe weather and atmospheric variables, such as solar radiation and wind at turbine height, up to 15 days ahead, with about 20% improvement in accuracy over conventional models.

Despite these successes, AI-based weather models have limitations. A University of Chicago study found that while neural networks excel at short-term forecasting, they struggle to predict unprecedented "gray swan" events, such as 200-year floods or historically rare extreme events. This highlights a key challenge: gaps in training data and the need for hybrid modelling approaches that combine the strengths of both AI and traditional physics-based model.

AI-driven climate models

Traditional climate models, like general circulation models (GCMs), have been crucial in simulating the Earth's climate system. However, these models often have limitations in spatial resolution and struggle to accurately represent complex of environmental interactions. AI offers a powerful solution to these limitations by integrating high-resolution datasets, such as those derived from satellite imagery, into climate modelling frameworks. Furthermore, AI can significantly improve downscaling techniques, which enhances the resolution and accuracy of regional climate projections. These projections are vital for informed local and regional decision-making, including policy formulation and infrastructure planning (Rolnick *et al.*, 2022; Rolnick, 2023).

AI can also augment the capabilities of GCMs through hybrid models that blend physical principles with data-driven AI techniques (Reichstein *et al.*, 2019). This synergistic approach improves the models' ability to simulate complex processes, such as cloud formation, ocean - atmosphere interactions, and carbon cycle feedbacks. These processes have historically challenging to model with high fidelity and precision (Reichstein *et al.*, 2019).

Scenario Planning with AI-Powered Models

Predicting future climate pathways

Scenario planning involves constructing plausible future trajectories based on varying assumptions concerning key drivers like carbon emissions, population growth, and technological advancements. Artificial intelligence (AI) significantly enhances this process by rapidly analysing large datasets and simulating numerous potential future pathways.

AI-driven scenario planning tools, such as reinforcement learning models, can optimize mitigation strategies by evaluating the effectiveness of different policy interventions under a range of simulated conditions (Silver *et al.*, 2018). For example, reinforcement learning algorithms have been used to identify optimal combinations of renewable energy investments, carbon capture deployment, and conservation policies that minimize long-term temperature rise while balancing economic and social factors.

Moreover, AI models have been successfully applied to simulate the impacts of various carbon pricing mechanisms or different renewable energy adoption rates on global temperature rise. These AI-driven simulations provide policymakers with a comprehensive assessment of trade-offs between economic costs and environmental outcomes, enabling evidence-based decision-making (Kumar *et al.*, 2024a). By integrating complex socio-economic variables with high-resolution environmental data, AI-powered scenario planning tools can produce more robust, adaptable, and context-specific climate strategies compared to conventional modeling approaches.

Regional and sector-specific scenarios

AI-powered simulations enable the development of more detailed, sector-specific climate change scenarios. The agricultural sector, for example, exhibits significant vulnerability to climate change. AI models can effectively simulate crop responses to varying temperatures, water availability, and CO_2 concentrations, which helps optimize planting schedules, crop selection, and irrigation practices (Peng *et al.*, 2020). Similarly, AI can simulate the impacts of climate change on urban infrastructure, coastal communities, and energy grids, providing localized insights that traditional models may overlook.

Disaster risk reduction and management

AI's capacity to enhance disaster risk management is one of its most significant contributions to climate change scenario planning. AI models predict the occurrence and intensity of extreme weather events like wildfires, floods, and storms. By integrating real-time data from satellites and sensors with historical datasets, these models simulate potential disaster scenarios, which improves preparedness and mitigation efforts (Tiggeloven *et al.*, 2025). These models are particularly valuable in predicting the cascading effects of climate disasters. For example, an AI model can simulate how drought conditions may increase the risk of wildfires, which can subsequently lead to biodiversity loss and air quality degradation. AI-powered simulations of such complex interdependencies are crucial for governments and organizations in developing effective adaptation and mitigation strategies.

AI for Climate Adaptation and Mitigation

AI in renewable energy optimization

Renewable energy sources, such as solar and wind power, are crucial for mitigating climate change. However, their intermittent nature presents challenges for grid integration. AI algorithms excel at forecasting energy demand and supply fluctuations, enabling more efficient integration of renewable energy sources. These forecasts allow for better grid management and reduce reliance on fossil fuels (Alam *et al.*, 2022). Furthermore, AI plays a vital role in the development and management of smart grids. Smart grids leverage AI to dynamically adjust energy distribution based on real-time demand, minimizing energy wastage and maximizing the efficiency of renewable energy systems (Rolnick *et al.*, 2022).

AI in carbon sequestration and capture

Beyond optimizing energy use, AI is instrumental in advancing carbon capture and storage (CCS) technologies (Rolnick *et al.*, 2022). AI algorithms can be employed to model and optimize the entire CCS process, including CO_2 capture, transportation, and storage, thereby enhancing the scalability and efficiency of these crucial technologies. Additionally, AI is playing an increasingly important role in monitoring natural carbon sinks. By analysing satellite imagery and other relevant data, AI algorithms can track carbon fluxes, detect deforestation, and monitor ocean acidification, providing valuable insights for effective carbon management strategies (Kazemifar, 2022).

Precision agriculture for climate adaptation

AI is transforming agriculture by enabling precision farming practices. Precision agriculture utilizes AI-driven models to optimize the use of inputs such as water, fertilizers, and pesticides based on real-time environmental data. This not only enhances crop yields, but also minimizes resource wastage and reduces greenhouse gas emissions associated with agricultural activities. In regions particularly vulnerable to climate change, such as drought-prone areas, AI can empower farmers to adapt by providing tailored recommendations on crop selection, planting times, and irrigation techniques, thereby improving resilience to climate variability (Lu *et al.*, 2021).

Another important consideration is the high energy demand associated with advanced AI computation. Training and deploying large-scale machine learning and deep learning models-particularly those used for climate forecasting, optimization of renewable energy networks, or large-scale genomic analyses-can consume substantial computational power. This increased energy usage may partially offset the climate benefits these technologies aim to achieve, especially when powered by non-renewable energy sources. Therefore, improving the energy efficiency of AI systems remains a critical priority to ensure that AI-enabled climate solutions are both environmentally and economically sustainable.

Challenges and Ethical Considerations

While AI offers significant potential benefits in precision agriculture, several challenges and ethical considerations must be carefully addressed.

Data limitations and biases

AI models rely on high-quality and extensive datasets for accurate predictions. However, in many regions, data on crop performance, soil conditions, and climate variables may be limited, incomplete, or unavailable. This scarcity can lead to biases in AI models, potentially skewing projections for certain areas or populations (Rolnick, 2023). Moreover, the development and deployment of sophisticated AI models require significant computational resources, which can lead to substantial energy consumption and, ironically, contribute to carbon emissions.

In many developing regions, agricultural datasets are often scarce, inconsistent, or unavailable, which reduces the accuracy and reliability of AI-generated predictions for those environments. This is particularly critical for smallholder farming systems, where limited monitoring infrastructure and fragmented data severely restrict model performance. Additionally, unequal access to digital tools, sensors, internet connectivity, and computational resources creates disparities in who can benefit from AI-driven agricultural innovations. Another growing concern is transparency: many AI systems-especially deep learning models-operate as black boxes, producing recommendations without clearly explaining the underlying rationale. This lack of interpretability can hinder farmer trust, reduce adoption rates, and limit the practical application of AI-generated insights in agricultural decision-making.

Ethical implications

The application of AI in climate modelling and agricultural practices raises several ethical concerns. For instance, AI-driven decision-making processes may inadvertently marginalize vulnerable populations if the models prioritize efficiency over equity. Therefore, it is crucial to ensure that AI climate models incorporate social and environmental justice considerations, guaranteeing equitable distribution of benefits (Crawford, 2021). Furthermore, the use of AI in agriculture raises critical ethical questions regarding data ownership, privacy, and the potential socioeconomic impacts, particularly for smallholder farmers who may lack access to advanced technologies and digital infrastructure (Rose *et al.*, 2019).

Policy Recommendations and Future Directions

The major advantage of implementation lies in the ability of AI to optimize resource allocation, leading to higher yields and reduced environmental impact, thus creating a pathway toward sustainable, equitable, and resilient food systems. The major advantage of implementation lies in the ability of AI to optimize resource allocation, leading to higher yields and reduced environmental impact, thus creating a pathway toward sustainable, equitable, and resilient food systems. To fully realize the potential of AI in enhancing plant adaptation to climate change, robust policy frameworks and strong international collaboration are essential. Governments should prioritize investments in AI research, development, and deployment, particularly in developing countries where agricultural systems are most vulnerable to climate variability and extremes (FAO, 2022). Targeted funding programs could support capacity-building initiatives, including training farmers and agricultural extension officers to use AI-driven decision-support systems (Araujo *et al.*, 2023). Establishing standardized and interoperable data-sharing frameworks is critical to ensure that researchers, policymakers, and farmers have equitable access to climate, soil, and crop data, enabling informed decisions about adaptation strategies (Kamilaris and Prenafeta-Boldú, 2018). Policies should also address data sovereignty and intellectual property rights to protect local farming communities from exploitation (Tzachor *et al.*, 2022). Future research should focus on integrating AI with traditional ecological knowledge (TEK) to ensure culturally sensitive and locally adapted solutions (Reid *et al.*, 2021). Additionally, the use of AI to develop climate-resilient crop varieties should be paired with the promotion of regenerative agricultural practices, such as cover cropping and reduced tillage, to create a holistic resilience framework (Ray *et al.*, 2019). A critical implementation challenge to be addressed through policy is the high energy demand associated with advanced AI computation (e.g., training large deep learning models). Policies must promote 'green AI' strategies focused on improving the energy efficiency of AI systems to ensure that AI-enabled climate solutions are environmentally sustainable.

Conclusions

AI is a catalyst for a paradigm shift in agriculture, moving from reactive, uniform practices to proactive, data-driven, and adaptive systems. The key innovative achievement of AI in this domain is its ability to create a unified, predictive framework that transcends traditional limitations. By integrating machine learning, the Internet of Things (IoT), remote sensing, and genomics, AI enables precision farming that's responsive to both micro-climatic conditions and global trends. Hybrid modelling further enhances forecasting accuracy, while AI-supported genetic engineering accelerates the development of climate-resilient crops. These achievements offer the undeniable prospect of strengthening global agricultural resilience and creating robust, resilient, and equitable food systems. However, harnessing AI's full potential requires addressing critical systemic challenges such as data and resource equity, ethical governance to ensure data sovereignty and fair decision-making, and sustainable integration to minimize its energy footprint. Moving forward, the convergence of AI, climate-smart farming, and participatory governance can drive resilient and equitable food systems. Secure global food security in an era of climate uncertainty requires addressing critical systemic challenges such as data and resource equity, the lack of model interpretability, ethical governance and sustainable integration to minimize its energy footprint.

Authors' Contributions

Conceptualization: HM, RYH, FAS, DSA, ASJ, KA, NIA, NMA, EF, LMS, AAH; Data curation: HM, RYH, FAS, DSA, ASJ, KA, NIA, NMA, EF, LMS, AAH; Formal analysis: HM, RYH, FAS, DSA, ASJ, KA, NIA, NMA, EF, LMS, AAH; Funding acquisition: HM, RYH, FAS, DSA, ASJ, KA, NIA, NMA, EF, LMS, AAH; Investigation: HM, RYH, FAS, DSA, ASJ, KA, NIA, NMA, EF, LMS, AAH; Methodology: HM, RYH, FAS, DSA, ASJ, KA, NIA, NMA, EF, LMS, AAH; Project administration: HM, RYH, FAS, DSA, ASJ, KA, NIA, NMA, EF, LMS, AAH; Resources: HM, RYH, FAS, DSA, ASJ, KA, NIA, NMA, EF, LMS, AAH; Software: HM, RYH, FAS, DSA, ASJ, KA, NIA, NMA, EF, LMS, AAH; Supervision: HM, RYH, FAS, DSA, ASJ, KA, NIA, NMA, EF, LMS, AAH; Validation: HM, RYH, FAS, DSA, ASJ, KA, NIA, NMA, EF, LMS, AAH; Visualization: XX; Roles/Writing - original draft: HM, RYH, FAS, DSA, ASJ, KA, NIA, NMA, EF, LMS, AAH; and Writing - review & editing: HM, RYH, FAS, DSA, ASJ, KA, NIA, NMA, EF, LMS, AAH.

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Conflict of Interests

The authors declare that there are no conflicts of interest related to this article.

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