**Climate-Smart Agriculture: AI-Based Solutions for Enhancing Crop Resilience and Reducing Environmental Impact**

**Abstract:** Climate change poses significant challenges to global food security, necessitating the use of AI-based climate-smart agriculture (CSA) technologies to improve crop resilience, reduce environmental impact, and optimize resource use. AI-based interventions can reduce carbon emissions by 30–50% and boost agricultural productivity by up to 25%. Machine learning approaches can forecast crop yields with 90% accuracy, facilitating climate adaptation. AI insect surveillance can reduce pesticide application by 30%, and artificial irrigation systems can save up to 40% water. IoT sensors and remote sensing improve soil health monitoring and carbon sequestration practices, increasing soil organic carbon stocks by 20–35%. AI-powered predictive analytics can provide early alerts for storms, reducing agricultural losses by 15–20%. Automation and robotics can reduce post-harvest losses by up to 35%. Blockchain and AI can ensure transparency in sustainable agricultural supply chains and carbon credit markets. This blending of AI and CSA can significantly reduce climate change implications. The use of AI in smallholder agriculture faces challenges such as inflated implementation costs, reduced digital literacy, and concerns around data privacy. Fixing these issues requires economical solutions, agricultural training initiatives, localized artificial intelligence models, and legislative changes.

**Keywords:** Artificial intelligence in agriculture, climate-smart farming, precision agriculture technologies, carbon footprint reduction, AI-powered predictive analytics.

**1. Introduction**

**1.1 Overview**

Climate change severely threatens agriculture globally, impinging on food security, productivity, and sustainability. Increased temperatures interfere with traditional planting seasons, changing crop yields and decreasing the amount of arable land (Yadav et al., 2021). Alterations in precipitation patterns result in droughts and floods, compromising water availability for irrigation. Severe conditions impair agricultural yields, diminish animal efficiency, and deteriorate soil quality (Padhiary & Kumar, 2024). Elevated temperatures promote pest and disease occurrences, enabling insects and diseases to flourish in previously hostile areas, so compromising crop health and raising dependence on pesticides. Agriculture accounts for around 25% of global greenhouse gas emissions due to deforestation, methane emissions from livestock, and the overuse of fertilizers (Ghosh et al., 2020). Climate-smart agriculture (CSA) is a sustainable framework that incorporates technological advancements, data-informed decision-making, and adaptable agricultural practices to reduce the negative effects of climate change.

**1.2 Climate-Smart Agriculture (CSA)**

CSA is a policy that aims at raising agricultural production, enhancing climate resilience, and reducing greenhouse gas emissions. It is promoted by organizations such as the Food and Agriculture Organization (FAO), and it aims to combine agricultural development with environmental sustainability (Mihret et al., 2025). The pillars of CSA are sustainable production growth, adaptation and resilience to climate, and greenhouse gas emission mitigation. CSA is a key to solving global food security, as the world's population is expected to exceed 9.7 billion in 2050 (Majhi et al., 2023). Implementing CSA practices increases efficiency, optimizes use of natural resources, and minimizes reliance on fossil fuel-derived products. It adopts global policy agendas such as the Paris Climate Change Agreement, the United Nations Sustainable Development Goals, and the European Green Deal, which promotes eco-friendly farming practices (Prandecki et al., 2021). By integrating technology with conventional farm knowledge, CSA supports small-scale farmers and industrial-scale agricultural organizations to attain stable production under varying climatic patterns.

**1.3 Purpose of AI in Enhanced Agricultural Sustainability**

Farm sustainability has been impacted by artificial intelligence (AI)in terms of data-driven decision-making, enhanced resource optimization, and enhanced resilience to climate change. AI applications in agriculture include predictive analysis, automatic monitoring, and precision agriculture (Vetrivel & Arun, 2025). Artificial intelligence enables farmers to predict and respond to climate variability with the aid of machine learning algorithms and big data analysis. Artificial intelligence-based meteorological prediction software processes huge volumes of data and provides precise climatic forecasts and helps farmers decide on planting time, irrigation time, and harvesting periods (Dhanke et al., 2024). Artificial intelligence-based climate risk-based early warning systems identify climatic risks that enable farmers to prepare well in advance. Artificial intelligence-based precision agriculture maximizes the utilization of critical inputs such as water, fertilizers, and pesticides. Intelligent irrigation monitors soil moisture and weather conditions to find the exact amount of water required and thereby prevents wastage and protects crops. Artificial intelligence-powered auto pest and disease monitoring detects the stress of plants at an initial level and lessens the usage of broad-spectrum insecticides.

AI-driven yield prediction models take previous and current information from sensor networks, satellite images, and remote sensing to offer the farmers accurate yield predictions (Ali et al., 2025). The outcome facilitates superior market planning as well as supply chain optimization, reducing wastage of food and ensuring improved profitability. AI optimizes supply chains with predictions of trends in demand as well as planning transportation optimization; thus, it reduces food distribution network carbon emissions. **Fig. 1** illustrates the contribution of AI in sustainable agriculture by way of optimum utilization of resources, least environment degradation, and enhanced food security. It is designed for precision agriculture, intelligent irrigation, detection of insects, estimation of crop yield, and monitoring of soil conditions. Use of AI reduces post-harvest losses and reduces carbon footprint.

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**Fig.1.** Purpose of AI in enhanced agricultural sustainability (Morchid et al., 2024)

**1.4 Objectives**

The article examinesAI-driven solutions in CSA to enhance crop resilience, maximize resource efficiency, and reduce negative environmental impacts. It addresses AI applications in climate adaptation, including predictive analytics and intelligent irrigation, and how AI reduces environmental degradation. It also addresses AI-driven precision agriculture, emission monitoring, and sustainable resource distribution. The paper examines issues in AI integration with CSA, including costs, data privacy, technological constraints, and farmer adoption. It also presents possible futures for AI in CSA, highlighting emerging trends and policy recommendations. The review takes into account AI technology, its uses, and the problems that emerge in CSA. It talks about combining machine learning and deep learning to make ourselves climate-change resilient, using IoT and remote sensing in precision agriculture, and using AI to make environmentally sound decisions by farmers.

**2. Methodology**

This study gives a structured way to look at the part AI-driven solutions play in CSA, with a focus on making crops more resilient and protecting the environment. The process includes five essential components: data collection, AI model selection, application and acceptance, assessment of effectiveness, and validation and scalability.

**2.1 Data Collection**

The process of collecting data for climate adaptation covers both primary and secondary sources. Primary data is obtained by IoT sensors, images from satellites, UAVs, and meteorological stations, which evaluate essential variables such as soil moisture, temperature, crop health, and environmental conditions. IoT sensors facilitate real-time monitoring, as satellite imagery helps in extensive evaluations of vegetation health, drought conditions, and pest infestations (Aziz et al., 2025). Weather stations monitor temperature, humidity, wind velocity, and precipitation, aiding climate adaptation measures. Secondary data comes from government papers, FAO and NASA databases, peer-reviewed journals, and agricultural research groups. It enhances AI-generated insights, assuring accurate estimates, preventive alert systems, and faster resource control.

**2.2Comparison of Literature Reviews**

The literature on AI-driven CSA reveals varying approaches, methodologies, and technological focuses. Ahmed (2025) focuses on Machine Learning, IoT, and Computer Vision for precision farming, yield prediction, and disease detection (Ahmed, 2025). While Yilmaz et al. (2025) explore Deep Learning techniques for plant disease detection and pest control (Yilmaz et al., 2025). Sharma et al. (2024) use Genetic Algorithms and Reinforcement Learning for resource optimization and smart irrigation, but lack scalability analysis (Sharma et al., 2025).Madhuri et al. (2023) apply Fuzzy Logic and AI-powered IoT for climate adaptation and automated farming, but fail to integrate hybrid AI models (Madhuri et al., 2025). The current study integrates ML, Deep Learning, Fuzzy Logic, GA, and Hybrid AI models to enhance real-time adaptation, scalability, and sustainability in CSA. This hybrid AI approach provides a comprehensive, adaptable, and scalable solution to address challenges in modern agriculture.

**2.3 AI Model Selections**

The paper examines various AI methodologies, including *machine learning (ML):* Decision trees, support vector machines (SVMs), and random forests are all types of supervised and unsupervised machine learning models. ML algorithms look into large datasets, find patterns, and help people make better decisions by using a wide range of environmental and agricultural variables (Cravero et al., 2022). Ensemble models, such as gradient boosting machines (GBMs) and extreme gradient boosting (XGBoost), substantially boost predictive accuracy. *Artificial Neural Networks (ANNs)*: It includes convolutional neural networks (CNNs) and recurrent neural networks (RNNs), which make it possible to diagnose diseases based on images and predict the weather using time series. CNNs are excellent at looking at satellite images, hyperspectral data, and thermal maps to find problems like insect infestations and water stress (Pfordt & Paulus, 2025). RNNs, particularly long short-term memory (LSTM) networks, provide precise predictions of climate trends and agricultural products. *Fuzzy Logic Systems*: These systems improve irrigation scheduling and pest management by reducing uncertainty in agricultural variables. Fuzzy logic models offer flexible, rule-based decision-making, increasing precision agricultural performance in altering situations. *Genetic Algorithms (GA)*: Itapplies GA to address various improvement challenges, including identifying the most effective fertilizer applications and crop rotation methodologies. GAs emulates natural selection to determine optimal solutions for resource allocation and production improvement (Şenaras et al., 2025). *Reinforcement Learning (RL)*: Improves precision agriculture automation by optimizing irrigation and nutrient application using adaptive learning. Reinforcement learning methods train AI-driven robotic devices and autonomous vehicles for instantaneous decision-making in agricultural management (Padhiary et al., 2024).

**2.4 Application and acceptance**

AI models are introduced into intelligent agricultural systems via cloud-based platforms, facilitating real-time data processing and decision-making (Shahab et al., 2025). These platforms combine big data analytics, AI algorithms, and IoT sensor networks, providing farmers with insights concerning crop health, soil conditions, and climate adaptation techniques (Padhiary, 2024). Edge computing decreases latency and relies on centralized cloud servers. AI-driven robots and automation facilitate precise agricultural activities such as irrigation, pest management, and harvesting (Onteddu et al., 2025). Autonomous tractors and drones utilize AI to identify crop illnesses, assess plant development, and administer fertilizers or pesticides with accuracy, thereby reducing resource waste and adverse environmental effects. Farmers can see real-time information about soil health, water use, and crop yields.

**2.5 Assessment of Effectiveness**

AI models in CSA get evaluated by several metrics to ensure reliability and precision. Root Mean Square Error (RMSE) and R² are used to test predictive models, especially those that predict crop production, evaluate soil health, and guess how climate change will affect the world. Precision-recall metrics and the confusion matrix serve in classification tasks such as plant disease diagnosis, pest identification, and crop quality evaluation(Upadhyay et al., 2024). It conducts field tests to verify the real-world effectiveness of AI-driven treatments.

**2.6 Validation and Scalability**

AI-driven CSA solutions are subjected to extensive pilot testing in various climatic conditions and areas to verify their practical utility. These works test AI models in real-time agricultural settings, evaluating their effectiveness across various soil types, climatic conditions, and crop kinds. AI models are judged on how well they can improve resource allocation, predict yields, and look at environmental effects in a range of agricultural industries (Liu et al., 2025). AI-driven solutions are implemented into current farm management systems, facilitating automated decision-making via cloud computing, IoT networks, and edge computing. AI models are more accurate now that they can learn new things all the time, which lets them adapt to new data and changing farming conditions (Sharada et al., 2025). This method makes a structured way to create resilient, adaptable, and long-lasting AI-powered climate-smart farming options.

**3. Climate-Smart Agriculture: Principles and Approaches**

**3.1 Principles of Climate-Smart Agriculture (CSA)**

CSA is a coordinated strategy for altering agricultural systems in a bid to lower climate change and provide sustainable food production. The Food and Agriculture Organization (FAO) describes it as an integrated approach that enhances productivity, enhances resilience to climate change, and reduces greenhouse gas emissions (Wijerathna-Yapa & Pathirana, 2022). The key principles of CSA include sustainability and efficiency, climate resilience, greenhouse gas emission reduction, evidence-based decision-making, and policy integration. Such principles are developed to promote resource-saving practices, enhance adaptive capacity of animals and plants to climate variability, and reduce the carbon footprint of agriculture. CSA utilizes artificial intelligence, remote sensing, and big data analysis to maximize sustainable farm practices. By integrating CSA practice with global and local policy, CSA is projected to deliver climate-resilient food systems favorable to large-scale business and smallholder farmers alike and ease pressures on the environment.

**3.2 Importance Components of CSA**

CSA aims to enhance crop production while preserving natural resources and reducing environmental deterioration. This subject matter covers precision agriculture, soil health management, smart irrigation systems, enhanced seed varieties, and sustainable livestock management. AI-driven techniques enhance the utilization of water, fertilizers, and pesticides, hence increasing agricultural yields and minimizing resource depletion (Thangamani et al., 2024). Climate adaptation measures aim to bolster the resilience of agricultural systems against climate-induced adversity such as droughts, floods, and severe temperatures. CSA promotes varied cropping systems, early warning systems, drought-resistant crops, water conservation methods, and climate-resilient livestock management. AI-driven monitoring systems assess animal health, thermal stress, and disease occurrences, enhancing livestock adaptation techniques (Bordignon et al., 2025).

Agriculture accounts for over 25% of worldwide greenhouse gas emissions, primarily due to methane emitted by cattle, nitrous oxide from fertilizers, and carbon dioxide resulting from deforestation and soil degradation (Filonchyk et al., 2024). CSA aims to reduce emissions by implementing precision fertilization, sustainable livestock management, carbon sequestration methods, alternative energy sources, and AI-based emission monitoring.

Applying climate-smart technologies in agriculture can substantially reduce global greenhouse gas emissions while preserving food production and economic stability. Methods include precision agriculture, cover cropping, organic amendments, biochar application, intelligent irrigation systems, genetic engineering, and AI-enhanced crop breeding, which facilitate the creation of climate-resilient seeds with improved resistance to drought, pests, and diseases

**3.3 Policy and Regulatory Frameworks Supporting CSA**

CSA is a global project that works for low-carbon and climate-resilient farming techniques that decrease global warming. It directly supports the United Nations sustainable development goals (SDGs) by facilitating sustainable food production. The European Green Deal (2019) targets the reduction of agricultural emissions, the promotion of sustainable farming practices, and the enhancement of biodiversity conservation (Prandecki et al., 2021). Governments globally are enacting national-level CSA policies, including India's national mission for sustainable agriculture (NMSA), the United States climate hubs initiative, and the Africa climate-smart agriculture alliance (ACSAA). Yet challenges include restricted finance, limitations to technological access and adoption, data privacy and ethical issues, and regulatory deficiencies in AI for agriculture persist (Dhillon & Moncur, 2023). Definitely scalability and success, governments must incorporate financial incentives, capacity-building initiatives, and AI-driven policy support technologies to promote CSA adoption. Despite these obstacles, CSA is a viable approach for enhancing sustainable agriculture and reducing global warming.

**4. AI in Climate-Smart Agriculture**

**4.1 Definition and Evolution of AI in Agriculture**

AI has converted agriculture by streamlining processes, enhancing resource use, and enhancing climate resilience. AI-based technologies assist farmers in forecasting weather, regulating soil and water resources, monitoring crop health, and enhancing inputs like fertilizer and pesticides. AI has progressed under three different waves: Traditional agriculture (prior to the 2000s), Precision agriculture (2000-2010s), and AI-powered smart agriculture (2010s-present) (Qian et al., 2025). AI-based solutions reduce environmental impact, increase climate change resilience, and enhance food security.

Sophisticated predictive algorithms can predict crop diseases, insect infestations, and weather conditions so that farmers can make real-time informed decisions. AI-based intelligent agricultural systems optimize the utilization of inputs by providing information regarding the duration and amount of water, fertilizers, and pesticides to apply based on the specific needs of crops (Padhiary, Hoque, et al., 2025). This improves the quality and amount of the harvests as well as the environmental impact and production cost. AI technology is applied by farmers to monitor and manage the health and welfare of their cattle. By means of camera and sensor data, AI systems can track the indicators that animals are ill or in distress, which can enable them to ask for assistance on time and stem disease outbreaks. This preventive action improves animal welfare and offers better quality and quantity of meat, milk, and other animal products.

**4.2 Types of AI Technologies Used in CSA**

ML and DL are branches of AI that allow computers to learn patterns from data and make predictions on their own, without explicit programming. CSA employs them to improve precision agriculture by minimizing waste, enhancing sustainability, and maximizing climate adaptation strategies (Kabato et al., 2025). Computer vision and remote sensing employ AI-driven image analysis to monitor agricultural fields, identify anomalies, and evaluate environmental conditions. In CSA, AI drones and cameras identify water stress, insect infestation, and nutrient deficiency in crops. AI weed identification technology separates weeds from crops and enables precision delivery of pesticides. Automated fruit grading involves description of fruits by size, ripeness, and quality to avoid post-harvest loss. Remote sensing in CSA employs AI-enhanced satellite imagery, hyperspectral imaging, and Geographic Information System applications to assess climate risks and enhance land-use planning (Janga et al., 2023). AI improves crop monitoring, resource optimization, and climate adaptation techniques through the application of computer vision and remote sensing.

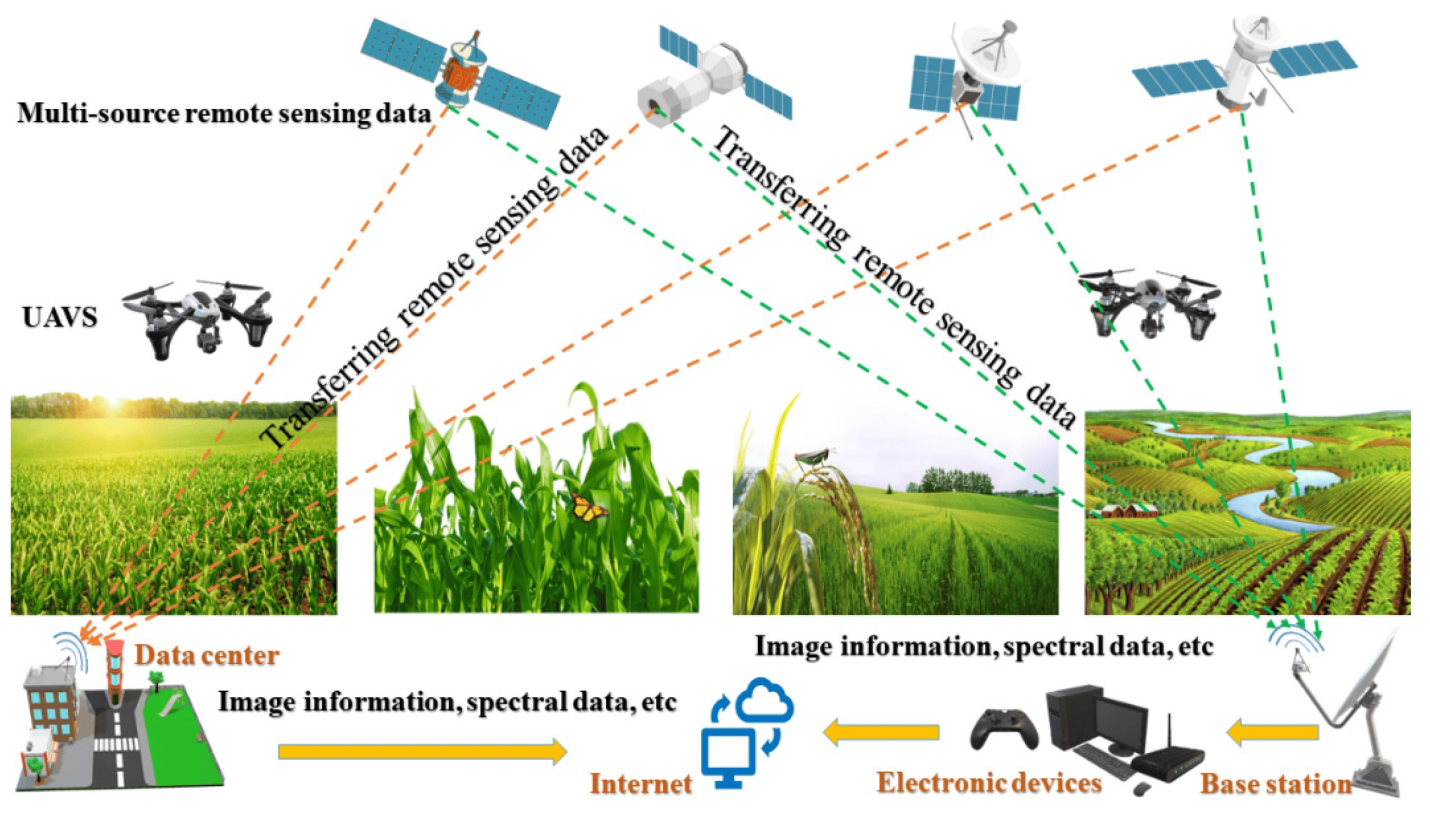
IoT makes real-time monitoring possible via smart sensors, drones, and automatic devices. IoT technologies with AI boost CSA by way of smart irrigation systems, precise livestock tracking, and autonomous greenhouse management. The synergy between IoT and AI enables data-driven decision-making, automates farms, and minimizes resource wastage (Mishra & Mishra, 2024). Big data analysis and predictive modeling allow AI to study enormous agricultural data from farms, sensors, and satellites to predict and optimize agricultural activities. AI-based climatic forecasting software analyzes previous climatic data to forecast droughts, floods, and severe weather conditions. Yield forecasting models estimate agricultural yields using edaphic factors, weather, and agricultural practices. Market analysis and logistics algorithms optimized by AI adapt supply chains, while GHG emission monitoring assesses carbon footprint on agriculture and supports climate-resilient agriculture.

**4.3 Advantages of AI Integration in Agriculture**

The formation of AI in CSA provides various advantages, such as increased productivity, enhanced climate resilience, sustainable resource management, effective pest and disease control, improved market access and supply chain management, and cost efficiency. AI-driven precision agriculture reduces input waste and improves crop yields, while automated monitoring systems facilitate real-time decision-making for farmers. AI-driven environmental predictions assist farmers in adapting to changes in the environment and enhance water use, hence reducing drought risks (Zidan & Febriyanti, 2024). AI-driven soil health monitoring ensures enduring agricultural sustainability. AI-driven early warning systems identify pest infestations and diagnose plant illnesses, whereas precise nitrogen management reduces nitrous oxide and methane emissions. AI-driven logistics enhance food distribution efficiency and reduce input costs while sustaining profitability (Agrawal & Kumar, 2025). But the use of AI faces difficulties, including substantial initial investment costs, inadequate digital infrastructure in developing nations, concerns over data privacy and security, and the necessity for farmer education and capacity enhancement.

**5. AI-Based Solutions for Enhancing Crop Resilience**

Climate change offers significant hazards to global agriculture, including crop yield, soil quality, and water resources. AI-driven solutions present novel approaches for improving crop resilience through climate risk prediction, resource optimization, and early alerts for severe weather events. It analyses the use of AI-driven predictive analytics in evaluating climate risks and improving agricultural adaptation techniques. **Fig. 2** highlights AI-driven technologies in climate-smart agriculture, including machine learning, deep learning, remote sensing, IoT sensors, predictive analytics, and robots. These technologies enhance crop monitoring, optimize resource utilization, and minimize climate risks, so reducing input waste, increasing yield prediction precision, and improving soil health management.



**Fig.2.**AI-based solutions for enhancing crop resilience (Wang et al., 2024)

**5.1 Predictive Analytics for Climate Risk Assessment**

AI is an incredible resource that utilizes machine learning, deep learning, and massive data analytics to forecast climatic threats and support decision-making. AI aids farmers in climate-related hazard prediction and taking preventive adaptation measures. AI-based climatic forecasting models provide accurate, localized, and real-time weather forecasts, which allow farmers to adjust planting times, irrigation, and fertilization methods to accommodate expected climatic conditions (Adewusi et al., 2024). These models utilize machine learning algorithms to analyze past weather patterns, satellite images, and meteorological trends to predict precipitation, temperature fluctuations, and drought. AI-powered climate dashboards offer farmers easy-to-use interfaces to track incoming weather dangers. For instance, Google's AI-based meteorological forecasting models utilize deep learning to provide nearly instantaneous weather forecasts, which reduces the risk of farming. The outcome increases accuracy in the identification of droughts, storms, and heat/cold waves, helps farmers make data-driven decisions regarding planting, irrigation, and harvesting, and reduces crop loss and wastage of water through improved planning.

Predictive models based on AI analyze the effect of climatic variability on crop yields so that farmers can modify their agricultural practices. ML algorithms analyze soil health, temperature variations, rain rates, and historical yield patterns to forecast future productivity. Computer vision and remote sensing technologies assess crop health through real-time satellite and drone imagery, detecting early signs of stress (Hoque et al., 2025). AI-based agronomic models suggest adaptation methods, such as drought-resistant crop varieties, planting schedules optimized, and water-conserving irrigation practices. Severe weather warning systems use AI analytics to forecast natural disasters and provide farmers with timely data. AI models based on satellites track meteorological anomalies and detect storms, heatwaves, and heavy precipitation. AI-based mobile apps warn farmers of impending weather threats, allowing for timely preventive measures.

**5.2 AI in Crop Disease and Pest Management**

Diseases and pest infestations significantly impact global crop production, resulting in lower yields and elevated chemical applications. AI-driven technologies provide early detection, planning, and decision-making capabilities to assist farmers in alleviating these risks and minimizing excessive pesticide use (Hoque, 2024). AI-driven image recognition for disease detection employs computer vision and deep learning algorithms to scrutinize crop photographs and accurately identify disease symptoms. Smartphone applications and AI-driven drones offer immediate notifications for first infections, whereas spectrum imaging and hyperspectral sensors identify subtle illness markers.

ML techniques for pest outbreak prediction utilize past pest outbreak data, meteorological circumstances, and soil health metrics to anticipate future infestations. Time-series forecasting methods utilize climatic and insect migration data to alert farmers to imminent outbreaks. AI-enhanced pheromone traps and remote sensors track pest activities and deliver real-time population assessments. Predictive modeling instruments evaluate the danger of locust swarms, autumn armyworm outbreaks, and aphid infestations (Yones & Ma’moun, 2025). AI-driven decision support systems (DSS) offer tailored, data-informed suggestions for the management of diseases and pests. AI chatbots and smartphone applications suggest suitable insecticides, fungicides, and biological control strategies. Cloud-based decision support system platforms combine weather information, edaphic conditions, and plant health to produce forecasts for pests and diseases. AI-driven robotic sprayers offer precise treatments exclusively in required areas, minimizing environmental effects. The advantages of AI-driven decision support systems include less chemical over application, savings in time and costs, and enhanced efficiency in crop health monitoring. **Table 1** showcases AI applications that help farmers adapt to changing climatic conditions, improve resilience, and optimize resource use.

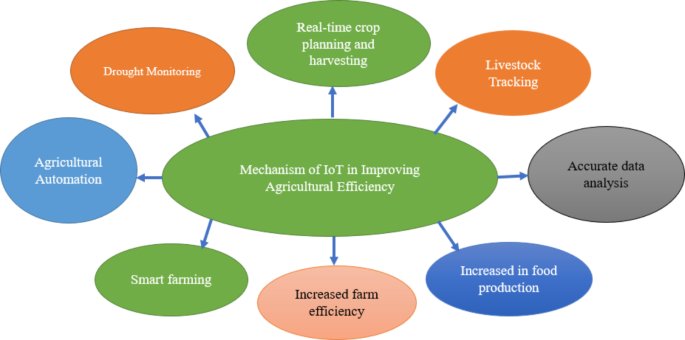
**Table 1.** AI applications for climate-resilient crop management

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| --- | --- | --- | --- |
| **AI Application** | **Function** | **Figures** | **References** |
| Drought stress monitoring | Identifies drought-prone zones | C:\Users\Azmirul Hoque\OneDrive\Desktop\1723280703050.png | (Kumar et al., 2024) |
| AI-guided crop breeding | Develops drought-resistant varieties |  | (Ansari et al., 2024) |
| Disease detection | Detects crop diseases early |  | (Abdullah et al., 2023) |
| Automated weather stations | Monitors microclimate changes | C:\Users\Azmirul Hoque\OneDrive\Desktop\511169_1_En_10_Fig1_HTML.png | (Arora & Gautam, 2022) |
| Yield prediction models | Estimates crop production based on conditions | C:\Users\Azmirul Hoque\OneDrive\Desktop\fpls-15-1417912-g001.png | (Agarwal & Tarar, 2021) |

**5.3 Precision Agriculture and Smart Irrigation**

Precision agriculture uses AI-driven analytics and IoT monitoring technologies to optimize the use of resources, enhance productivity, and minimize environmental impacts. AI- and remote-sensing-based smart irrigation systems help farmers manage water resources optimally in uncertain climatic conditions. AI-driven soil moisture monitoring uses IoT-enabled technology to monitor soil moisture continuously, suggesting accurate watering advice (Fuentes-Peñailillo et al., 2024). ML models forecast soil desiccation rates for improved water allocation. Satellite and drone imagery is used by remote sensing technologies to identify early indications of drought stress in crops. DL models and hyperspectral imaging evaluate leaf pigmentation variability, canopy temperature, and indicators of water stress. Cloud-based AI solutions give farmers drought warnings for immediate action.

AI-based irrigation optimization for water efficiency modulates the flow of water according to current agriculture requirements, weather conditions, and land quality (Wei et al., 2024). AI-enabled irrigation controllers apply ML concepts to decide on adequate watering schedules and rates. Cloud-hosted AI monitoring platforms allow remote access for management of farming operations by farmers. Internet of Things-enabled drip irrigation prevents wastage while providing optimal watering. NetBeat™ applies AI to optimize and automate irrigation schedules, thereby improving water efficiency. Advantages are minimized water wastage, improved agricultural production, and sustainable agriculture through data-based water management. **Fig. 3** shows AI-based precision agriculture and smart irrigation systems, improving crop yield by optimizing water and nutrient efficiency. It combines machine learning, IoT sensors, remote sensing, and predictive analytics to reduce water consumption by up to 40%, reduce wastage of fertilizers, and improve data-driven decision-making for efficient water and resource management.

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**Fig.3.** Precision agriculture and smart irrigation: AI-driven optimization (Duguma & Bai, 2024)

**5.4 Genomic AI for Climate-Resilient Crops**

AI-driven genomics and gene editing technologies are making it easier to make climate-resilient crop varieties that can handle more stress and produce more. AI-driven plant breeding for stress resistance uses ML techniques to discern ideal genetic features for drought, heat, and disease resilience. AI-driven phenotyping looks at how plants do in different environments, and automated breeding simulations guess how well breeding efforts will work. This technique expedites the creation of climate-resilient crops, diminishes dependence on traditional trial-and-error breeding methods, and bolsters food security amid shifting climatic conditions.

AI improves CRISPR gene-editing technology by expecting the most effective gene alterations to improve crop resilience (Sun et al., 2024). DL algorithms look at genetic information to find the right gene targets, and bioinformatics tools that are powered by AI make gene changes more accurate and effective. CRISPR-AI platforms facilitate the creation of drought-resistant, disease-resistant, and high-yield crops. Case studies on AI-assisted breeding initiatives include IBM Watson and Rice Genomics, Bayer's AI Breeding Platform, and the AI Projects at the John Innes Centre. Advantages involve expedited breeding initiatives for climate-resilient crops, decreased chemical usage, sustainable agriculture, and enhanced food security amid altering climatic conditions.

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**6. AI for Reducing Environmental Impact in Agriculture**

Agriculture significantly contributes to greenhouse gas emissions, deforestation, soil deterioration, and water pollution. AI-driven technologies can optimize resource utilization, diminish chemical inputs, and improve sustainability. This section examines the use of AI in sustainable resource management, the reduction of carbon footprints, and the reduction of food waste.

**6.1 AI in Sustainable Resource Management**

AI-driven precision-conceiving platforms enable farmers to deliver the appropriate quantity of nutrients at the ideal locations and timings, thereby decreasing environmental footprint and enhancing efficiency. ML methods evaluate soil nutrient condition through remote sensing and IoT-based soil sensors, while AI-driven decision support systems recommend proper fertilizer applications (Hoque & Padhiary, 2024). Drones and automatic applicators use artificial intelligence to deposit fertilizer only where it is required, preventing waste. Farming methods applied using AI reduce chemical usage but guarantee crop health. Image recognition pest-detecting systems installed with artificial intelligence selectively eliminate pesticide spray in the affected zones, and AI-linked automatic sprayers release precise chemical amounts. Forecast models predict the outbreaks of pests in the future and allow prevention from bio-biological control against chemical dosages.

In integrated nutrient management, AI improves nutrient cycles by taking into account the health of the soil, the needs of the crops, and the amount of available organic matter. AI-driven agricultural models evaluate nutrient uptake and recommend organic or bio-based fertilizers, and precision composting systems monitor and control the production of organic fertilizers. AI-driven farming platforms promote crop rotation and cover cropping practices to ensure soil fertility (Padhiary, Hoque, et al., 2025). Advantages of AI-based nutrient management are lower reliance on synthetic fertilizers, increased levels and diversity of microorganisms and soil organic matter, and reduced input costs and environmental pressure.

**6.2 AI and Carbon Footprint Reduction**

AI is a powerful tool for tracking and reducing greenhouse gas emissions caused by agricultural activity. It can estimate agricultural land and cattle farm-based emissions, employing IoT-enabled gas sensors to track methane and nitrous oxide in real-time. AI-driven emission models can assist governments in designing carbon-cut strategies, support sustainable agriculture, and enable businesses and farmers to achieve the target of carbon neutrality. AI can be applied to detect and monitor potential carbon sequestration in agriculture, including cover cropping, agroforestry, and soil carbon management. ML models predict the capacity of soil to store carbon with varying agricultural practices, while AI-powered satellite monitoring tracks carbon sequestration over time. Computerized decision systems encourage cover crops and no-till farming for enhanced carbon retention. Blockchain and AI can facilitate tracking of carbon credits in agriculture, creating transparent marketplaces for farmers adopting sustainable methods (Das et al., 2025). Carbon sequestration projects are verified by verification tools that are carried out by AI, and blockchain technology tracks and authenticates emission reductions so that all the stakeholders get a fair reward. Smart contracts allow carbon credit transactions to be automated, thereby preventing fraud. **Table 2** categorizes strategies aided by AI to promote sequestration in the soil, reduce emissions, and increase sustainable agriculture practices.

**Table 2.** AI applications for carbon sequestration in agriculture

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| --- | --- | --- | --- |
| **AI Application** | **Technology Used** | **Impact on Carbon Footprint** | **References** |
| AI for soil carbon mapping | Machine learning, GIS | Enhances soil carbon storage | (Acharya et al., 2022; Padhiary, Saikia, et al., 2025) |
| AI-optimized cover cropping | AI decision support systems | Increases soil organic matter | (Gupta et al., 2024) |
| Smart crop rotation | Predictive analytics | Enhances long-term soil health | (Getahun et al., 2024) |
| AI-driven agroforestry | AI & Remote sensing | Boosts carbon sequestration | (Mmbando, 2025) |
| AI-based biochar analysis | AI-Enabled soil sensors | Reduces soil carbon loss | (Atapattu et al., 2024) |
| AI-powered tillage management | Deep learning models | Minimizes soil carbon emissions | (Dubey et al., 2024) |
| AI for organic farming | AI-based crop models | Reduces chemical-based emissions | (Husaini & Sohail, 2024) |
| AI in regenerative Ag | AI & IoT sensors | Increases biodiversity & sequestration | (Sharma et al., 2024) |
| AI for precision composting | AI-driven microbial analysis | Improves soil carbon content | (Pace et al., 2025) |
| AI-integrated carbon trading | AI & Blockchain | Encourages low-carbon practices | (Odekanle et al., 2022) |

**6.3 AI for Sustainable Supply Chain and Food Waste Reduction**

AI food waste forecasting uses supply chain data, weather conditions, and market trends to forecast food surplus and waste patterns. ML algorithms estimate crop rot probability from temperature, humidity, and handling conditions. AI inventory systems optimize food distribution to reduce surplus stock generation. Grocery store AI forecasts demand, thus lowering food waste in stores. AI improves the efficiency of the food supply chain by optimizing harvest schedules, moving logistics, and storage conditions. AI-driven logistics solutions reduce delays and inefficiencies, whereas smart storage systems control temperature and humidity to prevent decay (Jackson et al., 2024). Blockchain technology facilitates the monitoring of food freshness and traceability. International Business Machines Corporation's Food Trust and AI-driven cold chain logistics reduce spoilage from farm to table, reducing food losses during travel and storage, ensuring high-quality produce for consumers, and lowering carbon emissions from food production waste.

AI-driven logistics enhance transportation efficiency, reducing fuel use and storage costs. Route planning reduces travel distances for food distribution, while automated warehouse systems monitor inventory levels. AI sensors in cold storage avoid food spoiling by regulating appropriate conditions. Google's AI-driven Freshness Algorithm assists retailers in monitoring food freshness and preventing waste; hence, decreasing transportation-related emissions, optimizing warehouse usage, and enhancing profitability.

**7. Challenges and Limitations of AI in CSA**

Although AI-driven solutions present significant potential for improving CSA, their execution encounters various technological, economic, and ethical hurdles. The widespread use of AI in agriculture is limited by the high costs of implementation, concerns about data privacy, the need to educate farmers, and problems with the ability of AI models to be scaled up and understood. This section examines these principal challenges and their effects.

*High expense and inaccessibility of AI tools:* AI farm tools, IoT sensors, drones, and robots are extremely costly to purchase with initial investments required, thus being inaccessible to small farmers. The cost of data collection, processing, and storage is extremely high, particularly in low-income regions. Broadband internet and cloud computing are not available in rural regions. Some of the potential solutions to this issue are government and NGO subsidies, creating low-cost AI alternatives, open-source AI platforms, and public-private collaborations (Agbeyangi & Suleman, 2024). These are measures intended to make AI-based agricultural solutions more affordable and accessible.

Data Privacy, Security, and Ethics Issues: AI technologies like soil health and production estimates hold farm data with commercial companies, raising issues of ownership of the data and its abuse. Absence of policy regulations may result in data monopolies, where big companies can own and benefit from the data of small farms (Atik, 2022). Enacting data protection laws, designing secure, networked AI data storage platforms, and setting up ethical AI governance are some of the solutions suggested. ML methods developed on biased datasets could favorably favor large-scale industrial farming at the expense of smallholder and indigenous farming systems. Automated decision-making systems have the potential to replace human judgment, possibly with undesirable effects on farmers.

An impetus for technical skill and farm education: That is correct, as most farmers in developing countries possess adequate technical skills to drive AI-based agriculture systems. That leaves a digital divide, whereby large, capitalized farms do well, but smallholders face a challenge in gaining training and maintenance. AI technology is usually susceptible to frequent upgrades and technical assistance, which the farmer may be unable to provide. Proposed solutions include government and private investment in AI training schemes, creation of affordable AI interfaces in local languages, and the use of mobile-based AI solutions to enhance accessibility for farmers (Chikatimarla & Rao, 2024).

Model Interpretability and AI Scalability Challenges: DL is utilized in AI-based agricultural models for disease detection and crop yield prediction, but the models are not always open, with farmers and policymakers unable to trust them and adjust their advice accordingly. In order to address this issue, one needs to develop explainable AI (XAI) models that give simple reasons for recommendations and employ visual dashboards to extract natural insights. AI models that are trained on agricultural data from a specific area are most likely to have low performance when they are implemented on different climates or soils, hence making them difficult to scale in different agroecological zones (Linus et al., 2023).

*Challenges of AI Adoption in Smallholder Farming:* AI-driven CSA meets difficulties in smallholder farming due to raised technology prices, limited digital literacy, and inadequate data availability. AI models require large datasets; yet, smallholder farms often lack the necessary historical data and digital records. Erratic internet connectivity and low energy infrastructure limit access to AI platforms. AI solutions must be adapted to the specific contexts of smallholder farms, as their conditions vary greatly; also, issues about data privacy, ownership, and trust influence adoption rates (Gavai et al., 2025). To enhance AI adoption, it is essential to establish methods such as economical solutions, agricultural training initiatives, mobile-based AI applications, and regional AI models. Cooperative effort among governments, NGOs, and agritech firms is essential to render AI-driven CSA accessible, scalable, and sustainable for smallholder farmers.

**8. Further Actions and Thoughts**

The addition of AI to CSA is ongoing, with substantial prospects for enhancement. The next steps for AI-driven CSA solutions will prioritize improving accessibility, enhancing computational capabilities, and ensuring ethical and sustainable practices. It explores significant technology innovations, operational methods, and policy suggestions for the future of AI in CSA.

Advancements in AI-CSA Integration**:** Future AI algorithms for CSA will need to be more accurate, flexible, and scalable, using data from satellites, IoT sensors, drones, and climate models. As reinforcement learning and generative AI get better, it will be easier to copy how farms react to changes in the weather. AI-driven agricultural phenotyping algorithms will discern genetically durable crops through the analysis of real-time environmental data (Angidi et al., 2025). Edge AI, operating on local devices, reduces latency and internet reliance, enhancing AI accessibility for remote agricultural operations.

Potential of Quantum Computing and AI in Agriculture: Quantum computing can enhance climate prediction and crop modeling by enabling fast climate risk simulations, which help farmers and policymakers make informed, long-term agricultural decisions. AI-driven quantum simulations may predict ideal crop genetics and breeding methods for climate resistance. Quantum AI can optimize agricultural resource allocation for sustainable farming by balancing water usage, soil health, and crop yield (Mohamed, 2023). Responses could involve research funding in quantum-AI applications and collaboration among AI specialists, climate scientists, and agriculture researchers.

Enhancing AI Adoption in Smallholder Farms: The development of AI in CSA relies on the creation of cost-effective and scalable technology for smallholder farmers. Governments and NGOs ought to finance AI-driven agricultural technologies to enhance affordability. Educational initiatives must enhance digital literacy among farmers, while extension services ought to incorporate AI-driven decision-support tools for fast resolution (Shafik et al., 2025).

Policy Recommendations for AI-Driven CSA Implementation:Governments need to implement AI ethics regulations that ensure transparency, data protection, and fair participation in CSA. AI-driven agricultural policies have to prioritize the inclusion of smallholder farmers and the sustainability of the environment. The EU's AI Act governs AI uses in sustainable agriculture. Enhancing partnerships between the private and public sectors and investing in open-source AI platforms can expedite the use of AI in agriculture (El Alaoui et al., 2024). Proposed solutions cover AI innovation benefits for companies and multidisciplinary partnerships among AI developers, agronomists, and legislators.

**9. Conclusion**

AI-driven CSA offers innovative solutions for crop resilience, resource efficiency, and environmental impact reduction. It uses ML, remote sensing, IoT, and predictive analytics to facilitate precision agriculture, leading to productivity increases of up to 25% and reduced carbon emissions of 30-50%. AI-driven irrigation and pest management systems reduce water usage and pesticide application, promoting sustainable practices. AI-driven forecasting helps mitigate climate risks, reducing crop losses by 15-20% due to catastrophic weather phenomena. The combination of AI and blockchain ensures transparency in carbon credit trading and sustainable supply chains. Despite challenges like data quality, scalability, and affordability, AI-driven decision-making and automation will enhance CSA's contribution to global food security. Further research, government promotion, and farmer integration are essential for optimizing CSA's effectiveness across diverse agricultural settings. Collaboration between researchers, policymakers, and farmers is crucial for successful implementation of these innovations.

**Authors’ contributions**

The work was conducted equally by all authors. Each author reviewed and supported the final manuscript.

**Disclaimer (Artificial Intelligence)**

The author(s) hereby state that no generative AI tools, including Large Language Models (such as ChatGPT, COPILOT, etc.) and text-to-image generators, were utilized in the composition or editing of the present article.

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