

Emerging Technologies for Climate-Smart Agriculture: Opportunities, Challenges, and Future Directions

Leah Chebet Bunei¹, Rosephy Cheptoo Koskei² & Andrew Kipkebut³

1, 2 & 3 Department of Computer Science/Information Technology, Kabarak University, Nakuru, Kenya

Abstract

Climate change is placing growing pressure on agriculture, threatening productivity, food security, and rural livelihoods through heat, unpredictable rainfall, drought, floods, pests, and diseases. Climate-Smart Agriculture (CSA) offers an important pathway for building resilient and sustainable food systems. Emerging technologies including artificial intelligence and machine learning, the Internet of Things, remote sensing, drones, big data analytics, blockchain, cloud and edge computing, generative AI, and large language models can improve precision farming, climate-risk forecasting, crop monitoring, disease detection, resource management, supply-chain transparency, and farmer advisory services. Despite these benefits, widespread adoption is hindered by high costs, weak digital infrastructure, limited connectivity, inadequate technical skills, cybersecurity concerns, poor data governance, and unequal access, especially among smallholder farmers in developing countries. Future progress requires affordable, interoperable, transparent, and sustainable technologies, supported by effective policies, capacity building, responsible data management, and collaboration. Farmer-centered innovation will be essential for achieving inclusive, productive, and climate-resilient agriculture.

Keywords: *Climate-Smart Agriculture, artificial intelligence, Internet of Things, remote sensing, big data, generative AI and climate resilience.*

1. Introduction

Climate change has become one of the most significant threats to the sustainability of agricultural and food systems worldwide. Changes in temperature, precipitation, water availability, and the frequency and intensity of extreme weather events are altering the conditions under which agricultural production takes place. Agriculture is particularly vulnerable because crop and livestock production depend directly on climatic and environmental conditions, including temperature, rainfall, soil moisture, and water availability (Intergovernmental Panel on Climate Change (IPCC), 2022). Climate-related hazards such as drought, heat stress, flooding, and shifting growing seasons can reduce yields, disrupt agricultural calendars, degrade natural resources, and increase production risks. The effects are especially important in regions where farming systems depend heavily on rainfall and where farmers have limited capacity to invest in adaptation. Evidence from global agricultural systems indicates that anthropogenic climate change has already reduced the growth of agricultural productivity, with substantial implications for food security and rural livelihoods (Ortiz-Bobea *et al.*, 2021).

The consequences of climate change are particularly pronounced among smallholder farmers in developing countries. Many smallholders operate under conditions characterized by limited access to irrigation, finance, agricultural inputs, extension services, markets, infrastructure, and reliable climate information. These constraints can reduce their ability to anticipate climate-related risks and respond effectively when climatic shocks occur. In sub-Saharan Africa, for example, the adoption

of climate-smart agricultural practices is influenced by a combination of socioeconomic, institutional, and biophysical factors, including access to extension services and information (Musafiri *et al.*, 2022). Consequently, strengthening agricultural resilience cannot depend solely on introducing new technologies. It requires integrated approaches that combine technological innovation with institutional support, farmer knowledge, appropriate policies, infrastructure, and access to relevant information.

Climate-Smart Agriculture (CSA) has emerged as an important framework for responding to these interconnected challenges. CSA seeks to address three broad objectives: sustainably increasing agricultural productivity and incomes, strengthening resilience and adaptive capacity to climate change, and reducing or removing greenhouse-gas emissions where feasible (Food and Agriculture Organization of the United Nations (FAO), 2013). Importantly, CSA is not a single agricultural technology or universally applicable package of practices. Its implementation depends on local environmental, climatic, economic, and social conditions. Practices that are effective in one farming system may not necessarily produce similar outcomes elsewhere. CSA therefore requires context-specific decision-making that enables farmers and agricultural institutions to select appropriate practices while balancing productivity, resilience, and environmental sustainability.

The growing complexity of climate risks has increased interest in digital technologies as potential enablers of CSA. Digitalisation can improve the collection, processing, communication, and use of agricultural and environmental information. Mobile services, remote sensing, digital advisory platforms, sensor networks, and data-driven decision-support systems can provide farmers and agricultural stakeholders with information that would otherwise be difficult or costly to obtain. In sub-Saharan Africa, digital agricultural technologies have been associated with opportunities to improve access to information, agricultural services, markets, and decision-support mechanisms, although adoption continues to be constrained by infrastructure, affordability, digital skills, and unequal access (Choruma *et al.*, 2024).

The emergence of Agriculture 4.0 has expanded these possibilities by introducing increasingly interconnected and data-intensive technologies into agricultural production. Agriculture 4.0 encompasses technologies such as artificial intelligence (AI), machine learning (ML), the Internet of Things (IoT), big data analytics, robotics, remote sensing, cloud computing, blockchain, and automated decision-support systems. These technologies enable agricultural systems to collect and analyse information from multiple sources and use the resulting insights to support more precise and timely management decisions (Klerkx & Rose, 2020; Rose *et al.*, 2021). Rather than relying exclusively on generalized recommendations or historical experience, data-driven agriculture can provide information that reflects changing field,

2. Problem Statement

Climate change continues to pose significant challenges to agricultural systems by reducing productivity, increasing the frequency of droughts, floods, pests, and diseases, and threatening global food security. Despite CSA having been practiced as an approach to enhance agricultural productivity, it is still inadequate to address the increasing complexity of climate variability. Emerging digital technologies such as AI, the IoT, remote sensing, robotics, blockchain, cloud computing, and big data analytics, have the potential to improve precision farming, climate adaptation, and resource-use efficiency.

The adoption of merging technologies in CSA remains limited, particularly among smallholder farmers in developing countries, due to inadequate digital infrastructure, high implementation costs, limited technical capacity, insufficient access to agricultural data, and weak institutional support. In addition, concerns related to data privacy, cybersecurity, algorithm transparency, and the ethical use of digital technologies present further challenges to their widespread implementation. Therefore, a comprehensive review of emerging technologies in CSA is necessary to synthesize current knowledge on their applications, opportunities, challenges, and future directions, thereby informing research, policy, and practice.

3. Objective of the Study

To examine emerging technologies for Climate-Smart Agriculture, with a focus on their opportunities, challenges, and future directions

4. Emerging Technologies for Climate-Smart Agriculture

Automation has highly revolutionized agriculture. Agriculture automation is the main concern and emerging subject for every country.

4.1 Artificial Intelligence and Machine Learning

Modern CSA relies heavily on two interconnected technologies: AI and ML. Broadly speaking, AI models human cognitive functions to tackle complex tasks like logical reasoning, sensory perception, and automated decision-making (Kisliuk et al., 2023). ML is a specialized branch of AI that drives this capability by training computers to extract underlying trends from data and refine choices without direct manual programming (Bishop & Bishop, 2024). Applied to CSA, these tools process multi-layered agricultural datasets to deliver precise forecasts and strategic recommendations, ultimately equipping farms to better withstand climate volatility.

One of the objectives of CSA is to enhance agricultural productivity and increase the incomes of smallholder farmers while promoting food and nutrition security through the sustainable management of land and natural resources, thereby reducing the need to convert forests into agricultural land (CGIAR, 2024). Achieving these objectives requires timely, accurate, and data-driven decision-making. Consequently, AI and ML have become important technologies in CSA because they can analyze large and complex agricultural datasets, identify patterns, and generate predictions and decision-support recommendations that help farmers optimize production, improve resource use efficiency, and adapt to climate variability.

Climate change has increased the frequency and severity of crop diseases due to changes in temperature, rainfall patterns, and humidity, hence threatening agricultural productivity and food security (IPCC, 2023; Savary et al., 2022). In response,

CSA promotes the adoption of innovative technologies that facilitate early disease detection and timely intervention to minimize crop losses while enhancing agricultural resilience (CGIAR, 2024). Generally, AI and ML have emerged as effective tools for plant disease diagnosis by analyzing images and field data to accurately identify diseases and recommend appropriate management practices (Kisliuk et al., 2023; Javaid et al., 2023).

Recent studies indicate that AI-based disease diagnosis systems employ machine learning and deep learning techniques, particularly Convolutional Neural Networks (CNNs), to detect diseases from images of leaves, stems, and fruits with high levels of accuracy (Kisliuk et al., 2023; Saleem et al., 2022). These models enable the differentiation of healthy and diseased plants, allowing farmers to implement timely disease management strategies before infections spread extensively (Saleem et al., 2022). Furthermore, AI-powered diagnostic models are increasingly being integrated into smartphone applications, making rapid, cost-effective, and field-based disease diagnosis more accessible to farmers, particularly in developing countries (Javaid et al., 2023).

The application of AI and ML in disease diagnosis supports the objectives of Climate-Smart Agriculture by reducing crop losses, improving productivity, minimizing excessive pesticide use, and promoting environmentally sustainable crop management practices (CGIAR, 2024; Javaid et al., 2023). Early disease detection also enhances farmers' resilience to climate-induced disease outbreaks by enabling timely decision-making and efficient resource utilization (Kisliuk et al., 2023). However, the literature highlights that the effectiveness of AI-based disease diagnosis depends on the availability of high-quality training datasets, reliable digital infrastructure, and locally adapted models capable of recognizing regional crop varieties and disease conditions (Kisliuk et al., 2023; Javaid et al., 2023).

Decision support is a fundamental component of Climate-Smart Agriculture (CSA) because it enables farmers to make informed decisions that enhance productivity, strengthen resilience to climate change, and promote the sustainable use of natural resources (CGIAR, 2024). Artificial Intelligence (AI) and Machine Learning (ML) have significantly enhanced Decision Support Systems (DSS) by enabling the analysis of large and diverse agricultural datasets, including weather forecasts, soil characteristics, satellite imagery, crop health, and market information, to generate timely and evidence-based recommendations (Kisliuk et al., 2023; Javaid et al., 2023).

Recent studies indicate that AI-driven decision support systems assist farmers in making critical decisions on planting dates, crop selection, irrigation scheduling, fertilizer application, pest and disease management, and harvesting strategies (Javaid et al., 2023; Boursianis et al., 2023). By identifying patterns within complex datasets, machine learning algorithms can predict crop performance, assess climate-related risks, and recommend optimal farm management practices that improve productivity while minimizing resource wastage (Kisliuk et al., 2023). The integration of AI with the Internet of Things (IoT), remote sensing technologies, and cloud computing has further strengthened decision support by enabling real-time monitoring of field conditions and providing location-specific recommendations for precision agriculture (Boursianis et al., 2023).

The application of AI- and ML-based decision support systems directly supports the objectives of Climate-Smart Agriculture by improving resource-use efficiency, increasing crop productivity, enhancing resilience to climate variability,

and reducing the environmental impacts associated with excessive use of water, fertilizers, and pesticides (CGIAR, 2024; Javaid et al., 2023). However, the literature also identifies several barriers to the widespread adoption of AI-powered decision support systems, including limited access to high-quality data, inadequate digital infrastructure, high implementation costs, and insufficient digital literacy among smallholder farmers, particularly in developing countries (Kisliuk et al., 2023; Boursianis et al., 2023).

4.2 Internet of Things (IoT)

The IoT refers to a network of interconnected physical devices equipped with sensors, software, and communication technologies that collect, transmit, and exchange data over the internet with minimal human intervention (Boursianis et al., 2023). In CSA, IoT enables continuous monitoring of agricultural systems by providing real-time information on environmental conditions, soil properties, crop growth, and resource utilization. This timely information supports precision farming practices that enhance agricultural productivity, strengthen resilience to climate variability, and promote the sustainable use of water, energy, and other natural resources (CGIAR, 2024; Boursianis et al., 2023).

Increasing water scarcity and unpredictable rainfall caused by climate change has been a major challenge in agricultural production. IoT-enabled smart irrigation contributes to sustainable agricultural production hence enhances farmers' capacity to adapt to climate variability. IoT-based smart irrigation systems use soil moisture sensors, weather stations, and automated controllers to monitor field conditions and regulate irrigation according to crop water requirements (Boursianis et al., 2023). Studies indicate that these systems improve water-use efficiency, reduce unnecessary irrigation, lower production costs, and increase crop yields while conserving water resources (Javaid et al., 2023).

In environmental monitoring, IoT devices are continuously used to collect data on environmental parameters such as temperature, humidity, rainfall, soil moisture, wind speed, and solar radiation, providing farmers with real-time information on changing field conditions (Boursianis et al., 2023). Continuous monitoring enables the early detection of climate-related risks, supports timely farm management decisions, and improves preparedness for extreme weather events, thereby enhancing agricultural resilience and sustainability (CGIAR, 2024; Javaid et al., 2023). Sensor networks have also been used whereby multiple sensors are connected and distributed across farms to monitor soil conditions, crop growth, water availability, nutrient levels, and environmental changes (Boursianis et al., 2023). These networks facilitate continuous data collection and transmission, enabling farmers to monitor field conditions remotely and respond promptly to changing environmental conditions. The literature suggests that sensor networks improve farm management efficiency, reduce resource wastage, support precision agriculture, and contribute to increased productivity while minimizing environmental impacts (Javaid et al., 2023). However, their adoption remains constrained by high installation costs, inadequate digital infrastructure, limited technical expertise, and concerns regarding data security and interoperability, particularly among smallholder farmers in developing countries (Boursianis et al., 2023).

Remote sensing has become an important tool in CSA by enabling the acquisition of information about the earth's surface without direct physical contact, typically through sensors mounted on satellites, aircraft, or unmanned aerial vehicles (UAVs) (Zhang et al., 2023). In CSA, remote sensing and satellite technologies provide timely and spatially extensive

information on crop conditions, soil moisture, vegetation health, and climatic variability, enabling farmers and policymakers to make informed decisions that improve productivity, strengthen climate resilience, and promote the sustainable management of natural resources (FAO, 2024; Zhang et al., 2023).

Crop monitoring is one of the most important applications of remote sensing in Climate-Smart Agriculture. Satellite imagery enables continuous observation of crop growth, vegetation health, and crop stress across large agricultural areas using vegetation indices such as the Normalized Difference Vegetation Index (NDVI) (Zhang et al., 2023). According to recent studies, remote sensing facilitates the early detection of nutrient deficiencies, pest infestations, water stress, and disease outbreaks, allowing timely interventions that improve crop productivity and reduce production losses (Karthikeyan et al., 2023). Furthermore, continuous crop monitoring supports precision agriculture by enabling efficient management of agricultural inputs and improving farm productivity.

Drought assessment is essential for improving agricultural resilience under changing climatic conditions. Remote sensing technologies provide near real-time information on rainfall patterns, vegetation condition, evapotranspiration, and soil moisture, enabling the early identification and monitoring of drought conditions (FAO, 2024; Zhang et al., 2023). The literature indicates that satellite-derived drought indicators support early warning systems, facilitate drought preparedness, and assist farmers and governments in implementing timely adaptation measures to reduce agricultural losses and enhance food security (IPCC, 2023).

Land-use mapping is another significant application of remote sensing in Climate-Smart Agriculture. Satellite imagery enables the classification and monitoring of agricultural land, forests, grasslands, and water resources over time, providing valuable information for sustainable land management and agricultural planning (Zhang et al., 2023). Studies have shown that accurate land-use maps support decision-making by identifying suitable areas for agricultural production, monitoring land degradation, detecting changes in land cover, and guiding climate adaptation strategies while minimizing environmental degradation (FAO, 2024). Consequently, remote sensing contributes to the sustainable management of natural resources, which is a key objective of Climate-Smart Agriculture.

4.4 Unmanned Aerial Vehicles (UAVs)

Unmanned Aerial Vehicles (UAVs), commonly referred to as drones, are aircraft that operate without an onboard pilot and are equipped with sensors, cameras, and positioning technologies for collecting high-resolution agricultural data (Tsouros *et al.*, 2023). In CSA, UAVs have emerged as valuable tools for improving agricultural productivity, strengthening resilience to climate variability, and promoting sustainable resource management through rapid, accurate, and cost-effective field monitoring (FAO, 2024). Their ability to capture real-time spatial information enables farmers to monitor crop conditions, detect field variability, and implement timely management interventions.

The UAVs help in health monitoring; they capture high-resolution images that enable the assessment of crop growth, vegetation vigor, nutrient deficiencies, water stress, and pest or disease outbreaks (Tsouros *et al.*, 2023). UAV-based monitoring facilitates the early detection of crop stress, allowing farmers to implement timely corrective measures that minimize yield losses, improve crop productivity, and enhance resilience to climate-related risks (Zhang *et al.*, 2023).

Precision spraying is another important application of UAVs in agriculture. UAVs equipped with precision spraying systems apply fertilizers, pesticides, and herbicides only to targeted areas, thereby reducing excessive chemical use and minimizing environmental pollution (Tsouros *et al.*, 2023). The literature shows that targeted spraying improves input-use efficiency, lowers labor costs, reduces farmers' exposure to agrochemicals, and enhances crop protection while supporting environmentally sustainable agricultural practices (Javaid *et al.*, 2023). This is particularly beneficial in difficult-to-access fields where conventional spraying methods may be inefficient.

Field mapping enables farmers to obtain detailed spatial information about agricultural land using high-resolution aerial imagery collected by UAVs. UAV-generated maps support the identification of field boundaries, topography, drainage patterns, crop variability, and areas affected by erosion or waterlogging (Zhang *et al.*, 2023). Such information assists farmers in planning land preparation, irrigation, input application, and other management practices that improve resource-use efficiency and agricultural productivity.

4.5 Big Data Analytics

Big data analytics is becoming an important component of Climate-Smart Agriculture (CSA) because it enables the collection, integration, processing, and interpretation of large and diverse datasets generated across agricultural systems. These datasets may originate from satellites, Internet of Things (IoT) sensors, unmanned aerial vehicles (UAVs), weather stations, remote sensing platforms, farm machinery, and digital farm-management systems. When analyzed collectively, such information can provide valuable insights into crop performance, soil conditions, weather patterns, resource availability, and climate-related risks. The ability to combine information from multiple sources allows farmers and other agricultural stakeholders to make decisions based on current and historical conditions rather than relying solely on experience or generalized recommendations. Big data analytics can therefore support yield improvement, efficient use of water and fertilizers, early identification of climate risks, and more sustainable management of agricultural resources. In this way, it contributes to the core objectives of CSA by supporting productivity, strengthening resilience to climate change, and reducing the environmental pressures associated with agricultural production (Zheng *et al.*, 2024).

One of the important applications of big data analytics in CSA is the improvement of climate and weather prediction. Agricultural decision-making is strongly influenced by the timing and intensity of rainfall, temperature variations, droughts, floods, and other extreme weather events. By combining historical climate records with satellite observations, weather forecasts, soil information, and data from real-time environmental sensors, advanced analytical systems can identify patterns and trends that may otherwise be difficult to detect. However, Artificial intelligence and machine learning can further enhance these analytical capabilities by processing large datasets and identifying relationships between climatic variables and agricultural outcomes. More reliable climate forecasts can help farmers determine suitable planting periods, select crops that are better adapted to expected conditions, plan irrigation, and prepare for potential climate-related disruptions. Consequently, data-driven climate forecasting can reduce uncertainty, improve preparedness, and strengthen the capacity of farming communities to cope with climate variability (Ma & Rahut, 2024).

Farm analytics involves the systematic collection and interpretation of farm-level data to improve the management of agricultural operations. Data obtained from IoT sensors, drones, GPS-enabled machinery, satellite imagery, and other digital systems can provide detailed information about soil moisture, crop health, nutrient availability, pest and disease occurrence, and water requirements. When this information is analyzed effectively, farmers can identify differences within their fields and apply inputs according to actual crop and soil requirements. For example, data-driven systems can support site-specific fertilizer application, targeted irrigation, early pest management, and better harvesting decisions. Such approaches can reduce unnecessary input use while maintaining or improving productivity. Farm analytics therefore contributes to greater resource efficiency, lower production costs, reduced environmental impacts, and improved resilience of agricultural systems (Shamshiri *et al.*, 2024).

Big data analytics strengthens agricultural decision-making by converting large and complex datasets into information that can be used by farmers, extension personnel, researchers, agribusinesses, and policymakers. Instead of treating agricultural conditions as uniform, data-driven decision-support systems can provide recommendations that reflect differences in weather, soil, crop condition, water availability, and farm management practices. At farm level, these systems can assist with decisions concerning planting dates, irrigation schedules, fertilizer application, pest and disease management, and harvesting. At a broader level, governments and agricultural organizations can use aggregated data to improve climate adaptation planning, food-security strategies, resource allocation, and agricultural value-chain management. The ability to transform data into actionable information therefore supports evidence-based decision-making and contributes to more productive, resilient, and sustainable agricultural systems (Zheng *et al.*, 2024).

4.6 Blockchain

Blockchain is an emerging digital technology with potential applications across agricultural value chains. It operates as a distributed digital ledger in which transactions and records can be securely stored, verified, and shared among authorized participants. Unlike conventional databases that are usually controlled by a single institution, blockchain allows multiple stakeholders to maintain access to a common record, thereby improving transparency and reducing opportunities for unauthorized alteration of information. In CSA, blockchain can strengthen the reliability and traceability of agricultural information while improving relationships among farmers, processors, distributors, retailers, financial institutions, and consumers. Its ability to create verifiable records can help reduce information gaps within agricultural value chains and improve trust among participants. These characteristics make blockchain relevant to food traceability, sustainable certification, supply-chain management, agricultural finance, and climate-risk management (Giganti *et al.*, 2024).

Food traceability is one of the most promising applications of blockchain technology in agriculture. Blockchain can be used to create a continuous digital record of agricultural products as they move through different stages of the value chain,

including input supply, production, harvesting, processing, storage, transportation, and retail. Such records can make it easier to establish the origin and movement of agricultural products and verify information relating to quality and production practices. In the event of food contamination, for example, traceability systems can help identify the source and location of affected products more quickly. Blockchain-based traceability can also help reduce fraud, improve consumer confidence, and support verification of sustainability and environmental standards. For CSA, these benefits extend beyond food safety. Transparent records can provide evidence that farmers and other value-chain actors are following environmentally responsible production practices. This can strengthen incentives for sustainable resource management and improve market recognition of climate-smart products (Giganti *et al.*, 2024).

Agricultural supply chains often involve numerous actors and transactions, making it difficult to maintain consistent and reliable information throughout the system. Blockchain can improve transparency by creating a shared digital record that allows authorized stakeholders to verify information about products, transactions, and their movement through the value chain. However, greater transparency can improve accountability and help identify inconsistencies, fraudulent activities, or disruptions more efficiently. It can also support verification of environmental, quality, and sustainability standards. For farmers, improved transparency may contribute to better market access and stronger relationships with buyers, while consumers can gain greater confidence in the origin and production practices associated with agricultural products. In the context of CSA, transparent and traceable value chains can improve the ability of agricultural systems to respond to climate-related disruptions, reduce post-harvest losses, encourage responsible sourcing, and strengthen collaboration among value-chain participants (Dal Mas *et al.*, 2023).

Smart contracts are digital agreements that automatically execute predefined actions when specified conditions are met. When integrated with blockchain, they can simplify agricultural transactions by reducing manual procedures and, in some cases, limiting the need for intermediaries. In agricultural value chains, smart contracts could, for example, automatically initiate payment once the delivery and quality of a consignment have been verified. Similar mechanisms could be applied to agricultural insurance, where predefined conditions based on trusted weather or satellite data could trigger an insurance payment following a verified drought, flood, or other climate-related event. These applications can reduce administrative delays, lower transaction costs, and improve confidence among farmers, buyers, insurers, and financial institutions. Smart contracts therefore have potential to strengthen agricultural financial services and improve mechanisms for managing climate-related risks. However, their effectiveness depends on reliable data, appropriate legal frameworks, and trusted digital infrastructure (Giganti *et al.*, 2024).

4.7 Cloud and Edge Computing

Cloud and edge computing provide important digital infrastructure for modern climate-smart agriculture. Cloud computing allows large volumes of agricultural and environmental information to be stored and processed on centralized computing platforms, while edge computing processes data closer to the location where it is generated, such as farms, sensors, tractors,

irrigation systems, and other agricultural equipment. The combination of these approaches can improve the speed, availability, and efficiency of agricultural data processing. When integrated with AI, IoT, remote sensing, and big data analytics, cloud-edge systems can support continuous monitoring, predictive analysis, automated responses, and more efficient farm management. These capabilities can contribute to higher productivity, improved adaptation to climate variability, more efficient resource use, and sustainable agricultural development (Javaid *et al.*, 2024).

Cloud computing provides flexible infrastructure for storing, managing, and analyzing large datasets generated by modern agricultural technologies. Information from IoT sensors, satellites, drones, weather stations, machinery, and farm-management platforms can be brought together within cloud-based systems and made available to authorized users. This centralized processing capacity allows researchers, farmers, agricultural organizations, and policymakers to analyze complex datasets without necessarily maintaining expensive local computing infrastructure. Cloud platforms can support the integration of information about climate, soils, crop performance, water availability, and input use, thereby enabling more comprehensive agricultural analysis. For CSA, improved access to data and analytical resources can strengthen climate-risk assessment, improve resource management, and support the development of adaptive farming strategies. However, the benefits of cloud computing depend on reliable connectivity, data security, affordable access, and appropriate digital skills (Sarker *et al.*, 2024).

Edge computing complements cloud computing by allowing data to be processed close to where it are generated. This is particularly useful in agricultural environments where decisions may need to be made immediately and continuous transmission of data to distant servers may be impractical. For example, edge-enabled systems can process information from soil-moisture sensors, temperature monitors, crop cameras, irrigation equipment, and other connected devices directly on or near the farm. This reduces communication delays and allows automated systems to respond rapidly to changing conditions. Real-time processing can support applications such as precision irrigation, early identification of crop stress, targeted input application, and rapid detection of environmental changes. By enabling faster responses and reducing unnecessary data transmission, edge computing can improve resource-use efficiency and strengthen farmers' ability to respond to climate-related risks (Javaid *et al.*, 2024).

The combination of cloud and edge computing provides an important foundation for intelligent agricultural applications. These technologies create the computing environment required for AI, machine learning, IoT networks, robotics, remote sensing, and big data analytics to operate effectively. Applications include automated irrigation, crop-health monitoring, disease and pest detection, yield forecasting, precision input management, and digital farm-management systems. Cloud platforms can support large-scale data storage and complex analysis, while edge devices can handle time-sensitive tasks at the farm level. The integration of these capabilities allows agricultural systems to move from reactive management toward more predictive and responsive approaches. By improving decision-making, reducing unnecessary input use, and

supporting timely interventions, cloud-edge architectures can contribute to higher productivity, greater climate resilience, and lower environmental pressures (Javaid *et al.*, 2024 & Sarker *et al.*, 2024).

4.8 Generative AI and Large Language Models

Generative artificial intelligence (GenAI) and large language models (LLMs) represent a relatively new stage in the digital transformation of agriculture. Unlike conventional analytical systems that primarily classify or predict outcomes, generative AI can produce text, explanations, summaries, recommendations, and other forms of content in response to user queries. In CSA, these capabilities could improve access to agricultural information and make digital advisory services more interactive and accessible. GenAI and LLMs can potentially combine information from weather forecasts, agricultural databases, scientific literature, farm records, and other sources to provide context-specific guidance. When connected with IoT systems, remote sensing, big data platforms, and cloud computing, these technologies could support more personalized and responsive agricultural services. Their value, however, depends heavily on the quality of the information provided to the system, the accuracy of its outputs, the availability of locally relevant data, and appropriate human oversight (Krupitzer, 2024).

Generative AI and LLMs have the potential to expand agricultural advisory services by providing farmers with accessible and interactive sources of information. Digital assistants, chatbots, and mobile applications can respond to questions concerning crop production, soil management, pests and diseases, weather conditions, and farm practices. An important advantage is the possibility of providing support beyond the operating hours or geographical limitations of conventional extension services. Farmers could receive information in a conversational format and potentially in local languages, making technical information easier to understand and apply. For smallholder farmers, such systems could complement rather than replace agricultural extension officers by providing basic and routine guidance while allowing human experts to focus on more complex cases. However, advisory systems must be carefully validated because incorrect or overly general recommendations could lead to inappropriate farm decisions. Human oversight and reliable agricultural knowledge sources are therefore essential (Ayre *et al.*, 2024).

Generative AI and LLMs may also improve the communication of climate information to farmers. Climate data can be technically complex and difficult to interpret, particularly when presented in the form of probabilities, models, or large datasets. AI-based systems can help translate this information into simpler and more actionable messages. For example, a system could combine weather forecasts, historical climate information, satellite observations, and crop-specific requirements to support decisions concerning planting dates, crop selection, irrigation, and preparation for extreme weather events. Such services could make climate information more useful at farm level by linking forecasts directly to agricultural decisions. Nevertheless, climate advisory systems should not generate recommendations independently of reliable

meteorological and agricultural information. Their effectiveness depends on accurate underlying data, appropriate localization, and mechanisms for verifying AI-generated outputs (Krupitzer, 2024 & De Clercq *et al.*, 2024).

Agriculture generates knowledge from many sources, including scientific research, extension materials, farmer experiences, government publications, weather information, and market reports. Generative AI and LLMs can assist in organizing, summarizing, retrieving, and communicating information from these diverse sources. For researchers and extension officers, AI-based knowledge systems could reduce the time required to locate and interpret large amounts of technical information. For farmers, they could simplify complex scientific recommendations and present them in more accessible forms. These capabilities could improve knowledge sharing and support faster dissemination of climate-smart practices. However, AI-generated information should be linked to credible sources and subject to appropriate validation because language models can produce inaccurate or misleading responses. Responsible knowledge management therefore requires a combination of AI capabilities, authoritative information, and human expertise (Krupitzer, 2024).

4.9 Challenges and Opportunities

The application of emerging technologies in CSA presents considerable opportunities to improve agricultural productivity, climate resilience, and environmental sustainability. AI, IoT, remote sensing, big data analytics, robotics, blockchain, and digital advisory platforms can improve the way agricultural information is collected, analyzed, communicated, and used. Together, these technologies can support more precise farm management, better resource allocation, early warning systems, and faster responses to climate-related risks. However, technological availability does not automatically translate into successful adoption. Farmers need access to reliable infrastructure, affordable technologies, relevant skills, secure digital services, and supportive institutions. These requirements are particularly important in resource-constrained environments, where the cost and complexity of advanced technologies can widen existing inequalities rather than reduce them. Consequently, the digital transformation of agriculture should be guided by principles of affordability, inclusion, sustainability, data protection, and farmer-centred innovation (Raj & Prahadeeswaran, 2025).

4.9.1 Challenges

According to Raj & Prahadeeswaran, (2025), the challenges are explained below:

i. Infrastructure: Adequate physical and digital infrastructure is a prerequisite for most smart agriculture technologies. IoT sensors, automated machinery, AI applications, cloud services, and digital advisory platforms depend on electricity, communication networks, computing facilities, and technical support. In many rural areas, these services remain unreliable or unavailable. Infrastructure deficiencies can therefore prevent farmers from using technologies consistently, even when suitable applications already exist. Investment in rural electricity, telecommunications, broadband networks, and digital agricultural infrastructure is consequently essential for expanding access to technology and strengthening climate resilience.

ii. Internet Connectivity: Reliable internet access is particularly important for cloud-based applications, digital advisory services, IoT systems, and real-time climate information. In areas where network coverage is weak, expensive, or intermittent, farmers may be unable to access digital services when they are most needed. Poor connectivity can also limit communication between sensors and centralized platforms, reducing the effectiveness of real-time agricultural applications. Expanding affordable broadband and mobile connectivity in rural areas is therefore critical for narrowing the digital divide and ensuring that smallholder farmers can participate in technology-enabled agriculture.

iii. Cost of Implementation: The initial and on-going costs associated with emerging agricultural technologies can be prohibitive for many farmers. Expenses may include purchasing sensors, drones, computers, automated equipment, software subscriptions, connectivity, data services, maintenance, and technical support. Smallholder farmers are particularly vulnerable to these financial barriers because they often operate with limited capital and face considerable production risks. Technology developers and policymakers should therefore emphasize low-cost, scalable, modular, and locally appropriate solutions. Financing mechanisms, cooperative ownership models, subsidies, and pay-as-you-use services may also help improve accessibility.

iv. Data Privacy and Cybersecurity: The digitalization of agriculture results in the generation and exchange of substantial amounts of data. Such information may include farm locations, production practices, financial information, soil characteristics, yields, machinery operations, and environmental conditions. The increasing volume and value of agricultural data creates risks associated with unauthorized access, cyber-attacks, data misuse, and unclear ownership. Farmers may be reluctant to adopt digital platforms if they do not understand how their information will be collected, stored, shared, or used. Strong data-governance systems are therefore required to clarify ownership and access rights, protect sensitive information, and establish appropriate cybersecurity standards.

v. AI Explainability: Many advanced AI and machine-learning systems operate as complex models whose internal decision-making processes are difficult for users to understand. This creates a challenge when AI recommendations influence important agricultural decisions such as disease treatment, irrigation, fertilizer application, or climate-risk management. Farmers are more likely to trust and use AI systems when they understand why a particular recommendation has been made. Explainable AI can therefore improve transparency by providing understandable reasons or evidence behind model outputs. Future agricultural AI systems should balance predictive performance with interpretability, particularly when decisions have significant economic or environmental consequences.

vi. Skills Gap: Limited digital skills remain a significant obstacle to the effective use of emerging agricultural technologies. Farmers, extension officers, and other agricultural stakeholders may lack the knowledge required to install, operate, interpret, maintain, or troubleshoot digital systems. Simply providing farmers with technology is therefore insufficient. Training and continuous capacity development is necessary to ensure that users can derive meaningful benefits from digital tools. Digital literacy programmes should be adapted to local conditions and should combine technical skills with practical agricultural knowledge.

vii. Policy and Governance: The rapid development of digital agriculture has created policy challenges relating to data ownership, privacy, cybersecurity, interoperability, AI governance, technology standards, and investment in digital infrastructure. Without appropriate regulatory frameworks, technological development may result in fragmented systems, unequal access, or misuse of agricultural data.

Governments and policymakers should therefore establish clear and flexible governance frameworks that encourage innovation while protecting farmers and other users. Effective policies should also promote interoperability between digital platforms and encourage investment in infrastructure, research, skills development, and inclusive agricultural innovation.

viii. Ethical Concerns: The adoption of emerging technologies raises broader ethical questions concerning fairness, inclusion, accountability, and potential discrimination. Technologies may disproportionately benefit farmers who already possess financial resources, connectivity, technical skills, and access to markets, thereby widening existing inequalities.

4.9.2 Opportunities

According to Javaid *et al.*, (2024), emerging technologies create significant opportunities for advancing climate-smart agriculture by improving productivity, increasing climate resilience, and promoting sustainable resource management. Smart farming technologies such as AI, IoT, big data analytics, and remote sensing enable farmers to monitor soil conditions, crop health, weather patterns, and resource use in real time. These capabilities support precision agriculture practices that improve input efficiency, reduce environmental impacts, and increase agricultural sustainability.

However, artificial intelligence and digital agricultural systems provide opportunities for improved climate prediction, early warning systems, and adaptive farm management. AI-based models can analyze climate and agricultural data to support decisions related to irrigation, pest management, crop selection, and resource allocation. These technologies strengthen farmers' ability to respond to climate variability and extreme weather events while improving productivity and resilience.

Furthermore, digital agriculture ecosystems create opportunities for improving knowledge sharing, strengthening agricultural extension services, and connecting farmers with researchers, markets, and policymakers. AI-powered advisory systems, mobile platforms, and digital services can provide location-specific recommendations and increase access to agricultural knowledge, especially among smallholder farmers. Future developments in sustainable AI, explainable AI, and integrated digital agriculture systems are expected to further enhance climate-smart agricultural transformation.

5.0 Results and Discussion

The review findings demonstrate that emerging technologies are becoming central drivers of climate-smart agriculture (CSA) by enhancing agricultural productivity, strengthening climate resilience, and improving sustainable resource management. Technologies including artificial intelligence (AI), big data analytics, Internet of Things (IoT), blockchain, cloud computing, edge computing, remote sensing, robotics, and generative AI are transforming conventional agricultural systems into intelligent, data-driven, and adaptive production models. These technologies contribute directly to the three primary objectives of climate-smart agriculture: increasing agricultural productivity, improving adaptation to climate

change, and reducing environmental impacts associated with agricultural production. However, their successful implementation remains influenced by critical factors such as digital infrastructure, affordability, technical capacity, data governance, policy support, and equitable access, particularly among smallholder farming communities in developing regions.

Artificial intelligence (AI) and big data analytics have emerged as among the most influential technologies supporting digital transformation in agriculture. AI-based systems enable advanced climate forecasting, crop disease detection, yield prediction, precision input management, and automated decision-making by analyzing complex environmental and agricultural datasets. Similarly, big data analytics integrates information from remote sensing platforms, weather monitoring systems, IoT sensors, and agricultural machinery to generate actionable insights for optimizing irrigation, fertilizer application, pest management, and farm productivity. These capabilities improve resource-use efficiency and enhance farmers’ ability to respond to climate-related risks. However, challenges related to data availability, computational requirements, algorithm transparency, technical expertise, and accessibility must be addressed to ensure responsible and inclusive adoption.

The findings further indicate that blockchain, cloud computing, and edge computing are contributing to the development of more efficient, transparent, and connected agricultural systems. Blockchain applications enhance food traceability, supply-chain transparency, certification processes, and stakeholder trust through secure digital records. Cloud computing supports large-scale agricultural data storage, analytics, and digital farm management platforms, while edge computing enables real-time processing of agricultural data closer to the point of collection. Despite their potential, adoption remains constrained by limited connectivity, cybersecurity concerns, high implementation costs, and inadequate digital infrastructure, particularly in low-income agricultural regions.

Emerging technologies such as generative artificial intelligence (GenAI) and large language models represent a new phase of agricultural digital transformation. These technologies offer opportunities for developing intelligent farmer advisory systems, improving access to agricultural knowledge, supporting climate information services, and strengthening digital extension systems. Through interactive communication and personalized recommendations, generative AI has the potential to improve decision-making and climate adaptation among farmers. However, challenges associated with information accuracy, misinformation, explainability, data privacy, ethical governance, and responsible deployment require further research before widespread agricultural application.

Table 1: Estimated Adoption Level (%) of Emerging Technologies for Climate-Smart Agriculture across Continents

Technology	Africa (%)	Europe (%)	North America (%)	South America (%)	Asia (%)	Key Observation
Artificial Intelligence (AI)	35	85	90	65	75	AI adoption is highest in North America and Europe due to advanced digital infrastructure, strong research capacity, availability of agricultural
						data, and automation capabilities. In Africa, AI applications are mainly focused on climate prediction, crop advisory systems, and pilot agricultural projects.

Big Data Analytics	40	85	90	70	80	Developed regions utilize big data for precision agriculture, predictive modelling, and farm management, while developing regions are expanding applications through satellite data, mobile platforms, and agricultural information systems.
Internet of Things (IoT)	30	90	88	60	75	IoT adoption is driven by smart farming systems, sensor-based monitoring, and automated agricultural operations. However, high costs, limited connectivity, and technical challenges restrict adoption in developing regions.
Remote Sensing and Satellite Technology	70	90	95	85	85	Remote sensing has the highest adoption globally due to accessible satellite data supporting crop monitoring, drought assessment, yield estimation, and climate-risk management.
Cloud Computing	35	85	90	65	80	Cloud-based agricultural platforms are widely established in developed regions, whereas adoption in developing regions depends on improvements in internet connectivity and digital infrastructure.
Edge Computing	20	70	80	45	60	Edge computing remains an emerging technology mainly applied in advanced smart farming systems requiring real-time agricultural data processing.
Blockchain	25	70	65	50	60	Blockchain adoption is mainly associated with food traceability, supply-chain transparency, certification, and agricultural trade systems.
Drones and Robotics	35	85	90	70	75	Adoption is highest in mechanized agricultural systems. Smallholder farming systems face challenges related to cost, technical skills, and maintenance requirements.
Generative AI and Large Language Models	15	60	70	40	55	Generative AI is an emerging agricultural technology with growing applications in advisory systems, knowledge management, and intelligent decision support.

Source: Adapted from FAO (2022), Meemken *et al.* (2024), Khanna *et al.* (2024) & Rose *et al.* (2021).

Table 1 above presents the estimated adoption levels of emerging technologies supporting climate-smart agriculture (CSA) across Africa, Europe, North America, South America, and Asia. The findings demonstrate significant regional differences in digital agricultural transformation, with adoption patterns strongly influenced by technological capacity, infrastructure availability, investment levels, research systems, and agricultural modernization.

North America recorded the highest overall adoption levels, ranging from 65% to 95% across the evaluated technologies, followed closely by Europe, with adoption levels between 60% and 90%. Both regions demonstrate advanced integration of artificial intelligence, big data analytics, IoT, cloud computing, remote sensing, drones, and robotics due to strong digital infrastructure, high agricultural mechanization, and substantial investment in agricultural innovation systems.

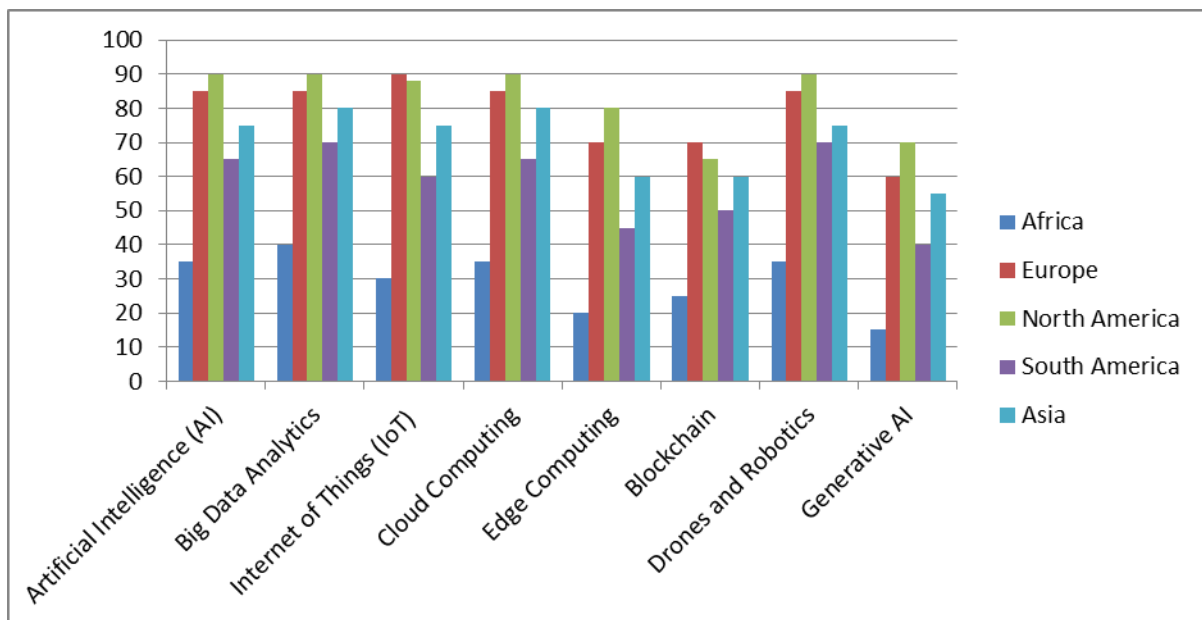
Asia demonstrated substantial progress in emerging agricultural technologies, with adoption levels ranging from 55% to 85%. High adoption of remote sensing (85%), big data analytics (80%), cloud computing (80%), AI (75%), IoT (75%), and drones and robotics (75%) reflects increasing investment in precision agriculture, digital farming platforms, and technology-driven agricultural development.

South America showed moderate adoption levels, ranging from 40% to 85%. Remote sensing recorded the highest adoption (85%), followed by big data analytics and drones and robotics (70%). However, adoption of advanced technologies such as edge computing and generative AI remains limited due to economic constraints, infrastructure gaps, and differences in technological readiness.

Africa recorded the lowest adoption levels across most technologies, ranging from 15% to 70%. Remote sensing demonstrated comparatively high adoption (70%), highlighting its suitability for climate monitoring, drought assessment, and agricultural planning in regions with limited conventional digital infrastructure. However, adoption of AI, IoT, cloud computing, blockchain, robotics, and generative AI remains constrained by limited connectivity, high costs, inadequate technical capacity, and insufficient investment.

Across all continents, remote sensing and satellite technology emerged as the most widely adopted technology, with adoption levels ranging from 70% in Africa to 95% in North America. Its widespread adoption reflects the accessibility of satellite data and its importance in crop monitoring, climate-risk assessment, and agricultural decision-making. Conversely, generative AI and large language models showed the lowest adoption levels, reflecting their recent emergence and the need for further development and validation within agricultural contexts.

Figure 1: Illustration of Significant Variations in Emerging Technology Adoption across Continents

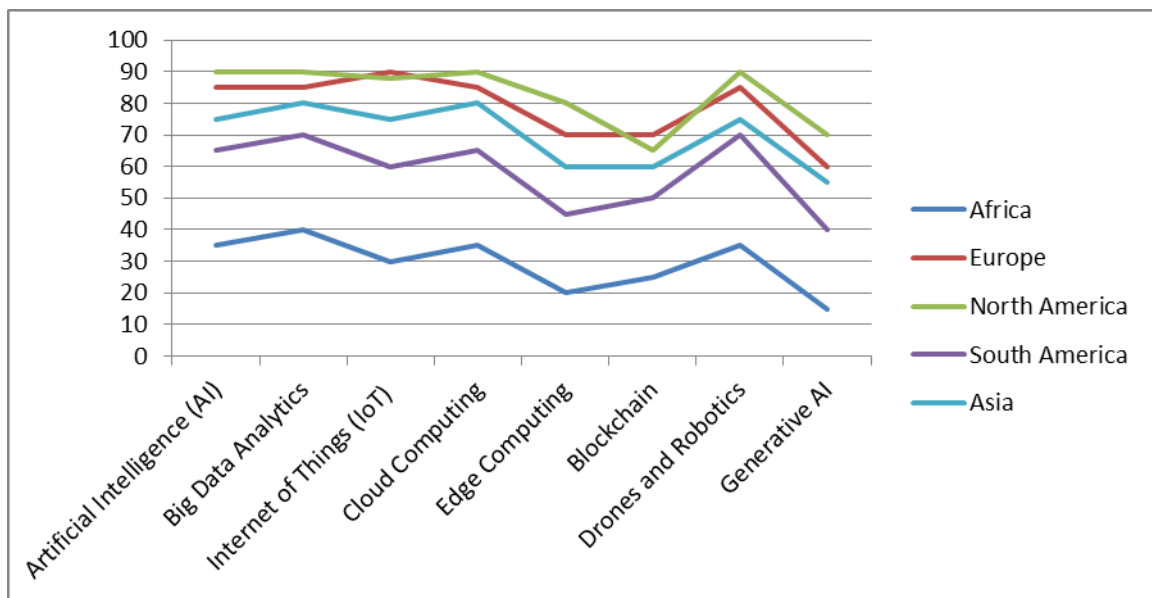


The column chart above illustrates significant variations in emerging technology adoption across continents. North America and Europe consistently demonstrate the highest adoption levels, supported by advanced digital infrastructure, strong research and innovation ecosystems, agricultural automation, and favourable technology adoption environments. These regions show particularly strong implementation of AI, IoT, big data analytics, cloud computing, drones, and robotics.

Asia and South America demonstrate intermediate adoption levels, reflecting growing investments in digital agriculture, precision farming, remote sensing applications, and agricultural information systems. However, differences in infrastructure development, investment capacity, and technical expertise influence the pace of adoption.

Africa shows comparatively lower adoption across most technologies, mainly due to connectivity limitations, affordability challenges, insufficient technical skills, and weaker digital agricultural infrastructure. However, the relatively high adoption of remote sensing highlights the potential of satellite-based technologies to support climate adaptation and agricultural decision-making in resource-constrained environments.

Figure 2: Adoption Trends of Emerging Technologies for Climate-Smart Agriculture across Continents



The line chart above demonstrates the adoption patterns of emerging agricultural technologies across continents. North America and Europe maintain consistently high adoption trajectories across most technologies, reflecting their leadership in digital agriculture, automation, and smart farming innovation.

Asia and South America show moderate but increasing adoption trends, particularly in remote sensing, AI applications, big data analytics, and precision agriculture. These trends indicate growing recognition of digital technologies as tools for improving productivity, resource efficiency, and climate resilience.

Africa remains at an early stage of digital agricultural transformation, with lower adoption trends for advanced technologies such as AI, IoT, blockchain, edge computing, and generative AI. Nevertheless, stronger adoption of remote sensing demonstrates opportunities for using accessible digital technologies to address climate-related agricultural challenges.

6.0 Future Research Directions

The rapid development of digital technologies is gradually changing climate-smart agriculture (CSA) from conventional data-based decision support toward more intelligent, interconnected, and increasingly autonomous farming systems. Technologies such as artificial intelligence (AI), the Internet of Things (IoT), big data analytics, cloud computing, blockchain, remote sensing, and robotics have already demonstrated considerable potential in improving agricultural productivity and climate resilience. However, several important research gaps remain, particularly in relation to scalability, interoperability, transparency, environmental sustainability, governance, and equitable access to technology. Addressing these gaps will be important for ensuring that digital innovation can effectively support agricultural systems facing increasing climate variability and resource constraints. The following areas represent important directions for future research.

6.1 Agentic Artificial Intelligence in Climate-Smart Agriculture

Agentic Artificial Intelligence (Agentic AI) represents an emerging development in intelligent agricultural systems. Unlike conventional AI applications that primarily provide predictions, classifications, or recommendations, Agentic AI has the potential to perceive changing conditions, reason across different sources of information, make decisions, and perform tasks with limited human intervention. Such systems could continuously respond to changes in weather, soil conditions, crop health, and farm operations while coordinating several digital tools simultaneously.

Future research should therefore examine how autonomous agricultural agents can be developed and safely deployed for applications such as precision irrigation, climate-risk prediction, crop monitoring, pest and disease surveillance, robotic harvesting, farm management, and dynamic allocation of agricultural resources. Research should also examine how these systems can learn from changing environmental conditions without compromising reliability or safety. Equally important is the development of governance mechanisms covering human oversight, accountability, transparency, cybersecurity, safety, and ethical use. Establishing appropriate safeguards will be necessary to ensure that autonomous AI systems remain trustworthy and beneficial to farmers and other agricultural stakeholders (Meemken et al., 2024).

6.2 Explainable Artificial Intelligence (XAI)

As agricultural AI systems become more sophisticated, the ability to understand and interpret their decisions is becoming increasingly important. Many machine-learning and deep-learning models can produce highly accurate results but provide limited information about how those results were generated. This lack of transparency can create uncertainty among farmers and other users, particularly when AI recommendations influence important decisions involving crop production, irrigation, disease management, or climate adaptation.

Future research should therefore focus on developing Explainable Artificial Intelligence (XAI) systems that combine high predictive accuracy with clear and understandable explanations. In climate-smart agriculture, explainable AI could strengthen users' confidence in digital recommendations, improve accountability, and support more informed decision-making. Research should also incorporate human-centred design principles so that explanations are understandable and useful to farmers with different levels of digital and technical knowledge. Developing XAI solutions that can operate effectively across different crops, farming systems, and climatic environments should be a major research priority (Dwivedi et al., 2023).

6.3 Quantum Computing for Agricultural Intelligence

Quantum computing is an emerging technological frontier with potential applications in solving complex agricultural and climate-related problems that may be difficult or time-consuming for conventional computers. Its future applications could include advanced climate and weather modelling, optimization of agricultural production systems, crop genetic analysis, supply-chain optimization, and simulation of complex environmental processes.

Further research is needed to determine where quantum computing can provide practical advantages in agriculture and how it could be integrated with existing technologies such as AI, remote sensing, digital twins, and big data analytics. Researchers should also assess the technological maturity, infrastructure requirements, financial implications, scalability, and accessibility of quantum-based solutions. Particular attention should be given to whether these technologies can eventually provide meaningful benefits in developing countries, where computing infrastructure and financial resources may be limited (World Economic Forum, 2024 & FAO, 2024).

6.4 Integrated Digital Agriculture Ecosystems

The future of climate-smart agriculture is likely to depend less on individual technologies and more on how different digital systems work together. AI, IoT, blockchain, cloud and edge computing, remote sensing, robotics, digital twins, and agricultural information systems can potentially form interconnected digital ecosystems capable of supporting continuous data exchange, predictive analysis, automation, and coordinated decision-making.

Future research should therefore prioritize the development of interoperable and secure digital platforms through which different technologies and stakeholders can communicate effectively. Such research should address data-sharing standards, cybersecurity, system compatibility, scalability, affordability, and digital inclusion. Particular emphasis should be placed on developing systems that can be used by smallholder farmers as well as large-scale commercial producers. Ensuring that digital ecosystems are accessible and affordable across different socioeconomic settings will be essential for preventing technological innovation from widening existing inequalities between agricultural communities (FAO, 2024 & World Bank, 2024).

6.5 Sustainable and Responsible Artificial Intelligence

The future development of digital agriculture should be assessed not only in terms of technological performance but also in relation to environmental, economic, and social sustainability. Sustainable Artificial Intelligence seeks to ensure that the benefits generated by AI are achieved without creating unnecessary energy consumption, carbon emissions, computational costs, or social inequalities.

Future research should investigate energy-efficient AI models, low-carbon computing systems, responsible data-management practices, privacy-preserving technologies, fairness-aware algorithms, and ethical approaches to automated decision-making. Researchers should also examine the environmental impacts associated with the entire lifecycle of AI-enabled agricultural technologies, from development and deployment to maintenance and disposal. In addition, appropriate policy and regulatory mechanisms should be investigated to ensure that AI development supports broader sustainability objectives while promoting inclusive, economically viable, and climate-resilient agricultural systems (UNESCO, 2024 & Vinuesa et al., 2024).

7.0 Recommendations

The effective integration of emerging technologies into climate-smart agriculture requires coordinated action from researchers, governments, policymakers, technology developers, farmers, private-sector organizations, and other agricultural stakeholders. Although technologies such as AI, IoT, remote sensing, robotics, blockchain, and big data analytics offer substantial opportunities to improve productivity, climate resilience, and resource efficiency, their benefits cannot be fully realized without appropriate infrastructure, governance, capacity development, investment, and stakeholder participation. The following recommendations provide practical directions for strengthening the responsible adoption of emerging technologies in climate-smart agriculture.

7.1 Recommendations for Researchers

Researchers should adopt interdisciplinary and trans disciplinary approaches that bring together agricultural science, climate science, artificial intelligence, data science, engineering, economics, and the social sciences. Such collaboration can support the development of technologies that are not only technically effective but also appropriate for specific farming environments and socioeconomic conditions.

Future studies should move beyond measuring technological accuracy or performance and examine issues such as affordability, scalability, environmental effects, social acceptance, long-term sustainability, and economic benefits. Greater attention should also be given to developing farmer-centred, explainable, locally adaptable, and resource-efficient technologies. Since smallholder farmers often face significant financial, infrastructural, and climatic constraints, research should explicitly consider these realities during technology development.

Farmers and local stakeholders should be actively involved throughout the research process, including the identification of problems, design of technological solutions, field testing, evaluation, and implementation. Participatory research can

improve the relevance of innovations, increase user acceptance, and strengthen the likelihood of successful long-term adoption (Meemken *et al.*, 2024).

7.2 Recommendations for Governments

Governments should create favorable conditions for digital transformation by investing in rural infrastructure, reliable electricity, broadband connectivity, digital agricultural platforms, and technology-enabled extension services. Public investment in agricultural research, innovation programmes, technology demonstration projects, and farmer training can help reduce the barriers that currently prevent many farmers from accessing emerging technologies.

Governments should also strengthen national climate information and early-warning systems so that farmers can access timely and reliable information about weather and climate risks. Digital literacy programmes should be expanded alongside agricultural training to help farmers understand and use emerging technologies effectively. Particular attention should be given to smallholder farmers and underserved rural communities to ensure that digital transformation does not benefit only large commercial farms. Strong institutional support will be essential for making digital agriculture more inclusive and accessible, particularly in developing regions (FAO, 2022 & World Bank, 2023).

7.3 Recommendations for Policymakers

Policymakers should establish clear regulatory and governance frameworks to guide the responsible development and use of digital technologies in agriculture. These frameworks should address important issues such as agricultural data ownership, privacy, cybersecurity, responsible data sharing, AI ethics, algorithmic transparency, and interoperability between digital systems.

Policies should also protect farmers from potential risks associated with inappropriate data use, technological dependency, digital exclusion, and unequal access to innovation. At the same time, regulations should avoid unnecessarily restricting technological innovation. A balanced policy environment is therefore needed one that encourages research and investment while protecting users and ensuring that digital agricultural development contributes to food security, sustainability, and climate adaptation objectives (Dwivedi *et al.*, 2023 & Arrieta *et al.*, 2020).

7.4 Recommendations for Technology Developers

Technology developers should focus on creating agricultural technologies that are affordable, easy to use, secure, explainable, adaptable, and appropriate for different farming conditions. Digital agricultural solutions should be designed around the actual needs and capabilities of their intended users rather than focusing exclusively on technological sophistication.

Human-centred design should be incorporated throughout the development process, with particular attention to interoperability, cybersecurity, energy efficiency, and long-term sustainability. Developers should work closely with farmers, extension officers, researchers, policymakers, and agricultural businesses when designing and testing new

technologies. Such collaboration can help ensure that digital solutions address genuine agricultural challenges and function effectively under real-world conditions.

Developers should also prioritize low-cost and scalable solutions for smallholder farming systems. Technologies that require expensive equipment, continuous high-speed connectivity, or highly specialized technical expertise may remain inaccessible to many farmers. Designing systems that can operate under resource-constrained conditions will therefore be important for achieving broader and more equitable technology adoption (Meemken et al., 2024).

7.5 Recommendations for Farmers

Farmers should be encouraged to participate actively in digital literacy programmes, agricultural training, field demonstrations, and technology-awareness initiatives. Developing practical knowledge of digital tools can enable farmers to make better use of AI advisory systems, IoT sensors, remote sensing services, precision agriculture technologies, and digital climate information.

When appropriately adopted, these technologies can support better farm planning, improve input-use efficiency, reduce production risks, and strengthen farmers' ability to respond to climate variability. Farmers should also make greater use of cooperatives, producer organizations, and other knowledge-sharing networks to exchange experiences and improve collective access to digital technologies.

Stronger relationships among farmers, extension officers, researchers, and technology providers should also be encouraged. Such collaboration can help ensure that technologies are adapted to local conditions, affordable for intended users, and capable of addressing the practical challenges faced by farming communities (Senyolo et al., 2024).

7.6 Recommendations for Multi-Stakeholder Collaboration

Scaling emerging technologies within climate-smart agriculture will require sustained collaboration among governments, researchers, policymakers, technology developers, financial institutions, private-sector organizations, extension services, farmer organizations, and civil society. No single stakeholder can independently address the infrastructure, financial, technical, institutional, and social requirements associated with digital agricultural transformation.

Multi-stakeholder partnerships should therefore support joint investment in digital infrastructure, research and development, innovation programmes, knowledge exchange, capacity building, and technology transfer. Such collaboration can accelerate the responsible deployment of AI, IoT, remote sensing, drones, blockchain, robotics, and precision agriculture while ensuring that technological development contributes to higher productivity, improved resource efficiency, climate resilience, and sustainable food systems (FAO, 2022 & World Bank, 2023).

Particular attention should be given to ensuring that digital agricultural innovations are inclusive and accessible to smallholder farmers, women, young people, and other potentially underserved groups. This can be achieved through targeted investments in digital literacy, farmer training, extension services, innovation hubs, demonstration farms, and accessible climate information platforms. Public-private partnerships and participatory technology development can further improve local ownership, increase adoption, and strengthen the sustainability of digital agricultural interventions (FAO, 2024 & Meemken *et al.*, 2024).

Finally, stakeholders should establish effective monitoring, evaluation, and governance systems to assess the performance and broader effects of emerging technologies. These systems should consider not only productivity outcomes but also data privacy, cybersecurity, interoperability, ethical AI, environmental sustainability, affordability, and social inclusion. Continuous monitoring can generate evidence for improving policies, guiding future investments, identifying unintended consequences, and ensuring that technological interventions remain aligned with the needs of agricultural communities. Such an approach will help ensure that emerging technologies contribute to productive, resilient, inclusive, and sustainable agricultural systems capable of responding to future climate challenges (United Nations, 2023).

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