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Artificial Intelligence-Driven Climate-Smart Agriculture in Africa: Pathways Toward Scalable Solutions for Sustainable Food Security in a Warming World.

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ABSTRACT

In Africa, where agriculture is the main source of income, one of the biggest threats to food security is climate change. A key tactic to guarantee resilience, lower gas emissions, and boost productivity is climate-smart agriculture, or CSA. The evolutionary impact of artificial intelligence (AI) in advancing climate-smart agriculture throughout Africa is examined in this paper. The relationships between artificial intelligence and climate smart agriculture research in general, as well as its applicability to adaptation initiatives in smart agricultural technology, are examined in this work. With data-driven methods to maximize resource utilization, reduce climate risks, and enhance decision-making, artificial intelligence (AI) has become a major enabler of climate-smart agricultural technologies (CSAT). The essay analyzes the potential applications of climate-smart agriculture and artificial intelligence technologies. It gave insight into how AI-powered tools, like decision-power systems, machine learning, and remote sensing, increase farming systems, anticipate yields, streamline value chains, and improve climate-risk prediction. Case studies were used, especially those from African nations like Nigeria, Kenya, and Zimbabwe. The study examines the advantages and disadvantages of adopting AI, such as limited financial resources, a lack of technical understanding and awareness of CSA techniques, low literacy rates, linguistic obstacles, and inadequate digital infrastructure. In order to ensure sustained food security throughout Africa, the report highlights the necessity of implementing climate-smart agriculture.

Keywords: Artificial Intelligence (AI), Climate-Smart Agriculture (CSA), Sustainable Food Security, Smart Agricultural Technologies (CSAT), Machine Learning, Remote Sensing, Resource Optimization, Digital Agriculture.

1.0 Introduction

Africa's Vulnerability to Climate Variability and Food Insecurity

Climate change poses a severe threat to global food security, and its effects are most noticeable in areas like West Africa where agriculture is the main economic activity and income source (Kinyua Gikunda, 2024). Africa's agricultural systems are extremely susceptible to soil erosion, diminished water supplies, and shifting weather patterns, all of which threaten food production and rural livelihoods (Roy et al., 2025). The Intergovernmental Panel on Climate Change (IPCC) claims that if adaptation measures are not put in place, rising temperatures and unpredictable rainfall could cause food yields in some African nations to drop by as much as 50% by 2050 (IPCC, 2022). A crucial strategy for improving resilience, cutting emissions, and guaranteeing food security in a warming future is climate-smart agriculture (CSA) (Mbeki and Keita, 2024). In order to maximize productivity of farming in the face of shifting climate circumstances, CSA combines resource-efficient technologies, creative data-driven solutions, and small scale farming practices (Kombat et al., 2021). Artificial intelligence (AI), one of these technologies, has demonstrated enormous potential to revolutionize the agricultural industry by facilitating precise resource management, real-time decision-making, and weather and crop performance prediction analytics (Gikunda, 2024). AI-driven CSA solutions include precision farming, automated irrigation systems, crop health monitoring, and climate forecasting tools, which together can enhance efficiency, decrease environmental impact, and increase the lifestyles of smallholder farmers (Roy et al., 2025). However, scaling these technologies across Africa presents significant challenges, including limited digital infrastructure, high costs, and the need for localized solutions tailored to diverse agro-ecological contexts (Kombat et al., 2021). Furthermore, farmers may reduce crop losses and improve harvest planning by using AI-driven prediction models to deliver accurate weather forecasts and assist them prepare for extreme heat waves, floods, and droughts (Gikunda, 2024). For instance, proactive irrigation management is made possible by ML algorithms that can examine satellite data to determine early indicators of soil deterioration and water stress (Roy et al., 2025). In places like East Africa, where early warning systems have lessened the impact of climate-related calamities, such technologies have shown promise (Kombat et al., 2021). Lastly, precision nutrient management is supported by AI in CSA, where sensors and data analytics enhance fertilizer delivery based on real-time assessments of soil health (Roy et al., 2025). This makes farming less harmful to the environment while increasing crop yields and soil fertility, resulting in a more sustainable agricultural system (Gikunda, 2024). However, substantial investments in digital infrastructure, farmer education, and supportive policies are necessary for the broad adoption of these technologies (Kombat et al., 2021).

Unique Ecological, Economic, and Infrastructural Contexts that Shape Agricultural Resilience

The problem of global food sufficiency and change in climate is centered in Africa. The continent is under tremendous pressure to modify its food systems because more than 60% of its people rely on rain-fed agriculture for a living, and climate change is making droughts, floods, and insect outbreaks more frequent and severe. However, this difficulty also offers a historic chance: Africa is in a unique position to advance beyond conventional agricultural development models by embracing digital innovation, especially artificial intelligence (AI), in order to create a future that is both food secure and climate resilient. Africa, the youngest continent, needs to use AI-driven Climate-Smart Agriculture (CSA) as a basis for equitable, sustainable development along with a means of mitigating climate risk, as its population is expected to double by 2050. Africa is a crucial region for the implementation of AI-driven CSA solutions due to its distinct ecological, economic, and infrastructure environments. Different strategies for agricultural development are needed for the continent's many agro-ecological zones, which range from dry to humid areas. Furthermore, the economic difficulties that many African nations face highlight the necessity of finding sustainable and affordable ways to address food insecurity. Opportunities to use AI in agriculture are also presented by the quick development of mobile technology and the expansion of access to digital services. Furthermore, Africa can contribute to the fostering innovation of AI solutions that are adapted to indigenous conditions rather than only benefiting from them. A revolutionary way ahead is provided by combining AI with farmer-led feedback mechanisms, participatory innovation, and indigenous knowledge. Co-designing technology with African institutions, farmers, and academics guarantees that CSA interventions are economically feasible, culturally appropriate, and socially rooted. Africa presents the possibility and the necessity to develop AI-driven CSA frameworks that are scalable, ethical, and fair as the globe moves to decarbonize food systems, establishing global standards for sustainability under climate stress. In conclusion, Africa is not only a continent that requires CSA reform, but it is also a rich environment for rethinking the ways in which AI might support food sovereignty, empower people, and promote climate resilience on a large scale. Africa's innovations, examples, and lessons might influence CSA efforts worldwide, particularly in other developing nations dealing with comparable issues.

Climate-Smart Agriculture (CSA)

The term Climate Smart Agriculture (CSA) refers to an integrated farming approach that reduces the related problems of food sufficiency and change in climate by managing agricultural resources and products—such as croplands, forests, livestock, crops, and fisheries—efficiently and methodically. It is also the process by which agricultural plans are created to provide sufficient food in the area of climate change. As a result, CSA seeks to accomplish the following objectives: making agricultural climate-adaptive, lowering greenhouse gas emissions wherever feasible, and raising productivity and incomes in a sustainable manner. Crops management, farms, rearing of animals, and aquaculture to establish a balance in food security and livelihoods is one of the four key components of CSA that help achieve these goals.

• UNK maintaining ecological services that are crucial for food security, agricultural development, adaptation, and mitigation through the management of landscapes and ecosystems.

• By offering managers of these resources services on climate impacts and mitigation measures, you can facilitate improved agricultural and land management.

• Using value chain interventions and demand-side strategies to increase the CSA's derived advantages.

Overview of CSA: its Threefold Objectives—Productivity, Adaptation, and Mitigation.

Pillar 1: Productivity

This key element, is most frequently materialized into product quantification (even in the FAO definition). However, concentrating only on output neglects two crucial pillar components: (1) Associating productivity with food security (and nutrition, one of its primary measures) is oversimplified. Increasing crop productivity can result in a decline in security of food and even malnutrition, as demonstrated by a number of cases in the literature (Fraval et al., 2019). For instance, adopting a high-yielding crop may result in a drop in the variety of crops grown. Campbell et al. (2016) also point out that CSA should include other aspects of food security in addition to productivity. The sustainability of food security is the second important factor. Although it doesn't specify how this should be measured, the definition of the food security pillar states clearly that advances in productivity and food security raise the need to be sustainable.

Pillar 2: Adaptation

Wiederkehr et al., (2018) recent review provides a great summary in the present situation of the art in assessments of climate change adaptation. One of their main findings is that the phrases "coping" and "adaptation" are frequently used interchangeably, making it difficult to define the idea of adaptation in many studies. In order to evaluate the frameworks' ability to manage both, we will take into account "short term adaptation," which reflects coping mechanisms, such as handling one-year weather irregularities or market instability, as well as pertinent dangers.

Pillar 3: Mitigation

One of the main CSA pillars is mitigation, which attempts to lessen the environmental (climate) impact of food production as

a) Globally, agriculture is the primary cause of degradation in the environment.

b) An important origin of anthropogenic GHGs, particularly in LMICs, is agriculture.

c) Numerous ecological services, such as carbon storage and biodiversity, can benefit from agriculture.

African-specific CSA challenges: Shortage of Labor Supply, Inadequate Farm Inputs and Materials, Limited Credit and Finance

One of the primary factors influencing choices in the majority of smallholder production systems is the availability of farm labor. Demand for labor is typically higher than availability, at least seasonally, in many parts of Africa. Due to under-nutrition and malnutrition, the dominance of HIV/AIDS and other diseases, and rural-urban migration (particularly among young males), labor is frequently in short supply. Dependency ratios, or the proportion of people who are not employed to those who are, are exacerbated by illness and poor health and are predominant in Africa than in any other part of the world (Radeksz, 2010).

Insufficient Farming equipment

Insufficient availability and affordability of seeds, inorganic fertilizers, pesticides, and herbicides restrict the application of CSA in a way that maximizes effectiveness (Milder et al., 2011). However, by encouraging biological processes and management strategies that increase the fertility of soil and suppress weeds and pests, CSA can increase yields in circumstances where agrochemicals are either unavailable or prohibitively expensive. Nitrogen-fixing plants, such as annual herbaceous plants like legumes, shrubs, or trees like Faidherbiaalbida, are necessary for most CSA systems. Intercropping with these plants improves yields, soil health, and soil chemical and biological properties by reducing weed and insect problems (Akinnifesiet et al., 2010).

Limited Credit and Finance

Smallholder farmers sometimes aren't able to use CSA techniques because they don't have the money to invest in land, equipment, manpower, seeds, breeds, and other farm inputs. In the long run, CSA is usually more profitable than conventional farming, according to Milder et al. (2011). However, achieving these long-term benefits requires an initial investment that is occasionally too expensive or risky for small farmers to undertake alone. Vulnerable farmers are especially risk averse due to worries about household food security, and there isn't much room for error.

Artificial Intelligence in Agriculture

Artificial intellect (AI) is a technology that attempts to mimic human intellect, including learning, problem-solving, and cognitively equivalent actions (Siemens et al., 2022). Intelligent software and systems are created by researching how the human brain works, including how it learns, makes decisions, and solves issues. These systems successfully mimic the human brain by being taught with data and producing desired outputs based on legitimate inputs. To address issues in agriculture, artificial intelligence (AI) uses a variety of methods, including computer vision, robots, the Internet of Things, deep learning, machine learning, and wireless sensor networks (WSN) (Khanna et al., 2019).

Machine and Deep Learning

Machine learning (ML), a specific area of artificial intelligence (AI), aims to enable computers and other machines to replicate human learning, complete tasks independently, and improve their accuracy and performance over time as a result of experience and exposure to more data. It can be divided into three primary categories: supervised learning, unsupervised learning, and reinforcement learning. Both the data and the corresponding labels, or replies, are sent to the learning algorithm in supervised learning. The goal of machine learning is to enable algorithms to learn from labeled data and produce accurate predictions for unlabeled data. This approach is frequently used in tasks including object recognition, probability estimation, and regression analysis (Grinblat et al., 2016). Specifically, CNNs or DCNNs are employed in the machine learning domain known as "deep learning." Unlike basic neural networks, deep neural networks feature several hidden layers and a hierarchical structure. They also use advanced neurons and methods like convolutions and multiple activations in a single neuron. These features allow deep neural networks to handle raw input data and automatically identify the representations required for the specific learning task (Filipi et al., 2019).

Remote Sensing

Remote sensing technologies provide an analytical capability that functions as an early warning system, allowing agricultural stakeholders to take prompt action to solve potential issues before they worsen and lower crop yields. Recent advancements in sensor technology, data management, and analytics have given the agricultural sector a wide range of remote sensing options. However, the complete adoption of these technologies has been impeded by a lack of understanding regarding their effectiveness, suitability, and economic viability

Computer Vision

Intelligent systems based on vision have become a part of almost every facet of contemporary human existence. These systems enable robots to replicate human visual and cognitive skills to make well-informed judgments about the work at hand by combining computer vision, artificial intelligence (AI), and machine learning technologies. While artificial intelligence (AI) technologies and machine learning algorithms are used to identify patterns and forecast actions, computer vision technology is used to analyze and interpret visual information from the surrounding environment. Over time, these intelligent systems learn to perform better. Since the late 20th century, automated vision-based technologies have transformed every industry. The 1950s saw the beginning of research on machines that could interpret visual input. Shakey, a revolutionary robot created at Stanford Research Institute in the late 1960s, is an example of one of the first intelligent robots (DARPA, 2024). The technique for optical character recognition was developed in the 1970s. The use of machine learning methods in the creation of vision-based intelligent systems became more prominent in the 1980s and 1990s. But these early systems, which were primarily rule-based, were relatively simple (Edem Gold, 2023). The performance of vision-based systems has greatly improved with the development of powerful computing resources, computer vision techniques such as object recognition and picture segmentation in the 2000s, and the introduction of deep neural networks in the 2010s. New clever machines that can detect and interact with their surroundings and carry out activities similarly to people being created at the nexus of the robotics and vision-based intelligent systems fields.

Robots

The advent of agricultural robots marks a new era in conventional farming and a paradigm shift in cultivation methods (Lagnelöv et al., 2021). These cutting-edge machines have become innovation accelerators by seamlessly integrating automation into the agricultural scene and revolutionizing long-standing procedures. In their efforts to address the many problems confronting the agriculture sector, these robots act as technical sentinels, introducing previously unheard-of levels of efficiency, precision, and sustainability.

Rationale for AI integration in CSA to Address Africa’s Agricultural Challenges

CSA is an integrated approach to managing agricultural systems that address climate change challenges while ensuring food security and fostering sustainable development (Bazzana et al., 2022; Hellin et al., 2023). It is characterized by three main objectives: first, to increase agricultural productivity and profits in a sustainable way, which will help ensure food safety and economic growth; second, to increase the ability of agricultural systems to endure and recover from shocks related to climate change; and third, to reduce or eliminate greenhouse gas emissions, which will lessen the adverse environmental effects on farming (Paul et al., 2023; Sawhney & Perkins, 2015; Zaman et al., 2021). Building a more robust and resilient agriculture sector that can thrive in the face of continuous environmental changes and climatic unpredictability is the aim of these interconnected goals. The foundation for robust and sustainable agricultural systems is provided by the three primary CSA pillars of productivity, adaptation, and mitigation. By enhancing agricultural systems' capacity to withstand and recover from climate-related stresses such droughts, floods, and shifting growing seasons, adaptation aims to protect the availability of food and livelihoods (Arif et al., 2020; Hellin et al., 2023). Furthermore, by reducing greenhouse gas emissions from agriculture through techniques like improved soil management, efficient water use, and ecologically friendly land-use practices, mitigation supports global efforts to address climate change (Schreiner-McGraw et al., 2024; Zaman et al., 2021).

Purpose and Scope of the Review

The purpose of this review is to critically analyze how artificial intelligence (AI) might be used to enhance Climate-Smart Agriculture (CSA) in Africa, a region that is particularly vulnerable to food shortages and climate change. Africa's farmers must find innovative and contextually sensitive solutions to the continent's degraded natural resources, erratic rainfall patterns, and warming temperatures. Artificial intelligence (AI) technologies, including as machine learning, remote sensing, predictive analytics, and intelligent decision-support systems, hold considerable promise for optimizing resource utilization, enhancing resilience, and increasing productivity within CSA settings. There are four main sections to this review: Introduction: The susceptibility of Africa to food insecurity and climatic variability Agricultural Resilience in Particular Ecological, Economic, and Infrastructural Contexts, Climate-Smart Agriculture (CSA): Definition and Objectives, and Artificial Intelligence (AI) in Agriculture. Methodology: Examine the Analytical Framework, Data Sources, and Strategy. Conclusion: Synthesis of AI's Role in Transforming CSA in Africa, AI as an enabler of adaptive, productive, and sustainable agriculture, Discussion of the Foundations and Practice of CSA in Africa, AI Techniques and Global Agricultural Applications, AI Applications for CSA in Africa, Barriers to AI Integration in CSA in Africa, and Strategies for Scalable and Inclusive AI-CSA Integration A call to action and the necessity of adapting AI-CSA tools to the socio-ecological conditions of Africa.

2.0 Methodology

Given the volume of data on CSA, a narrative review was thought to be more appropriate. A variety of search techniques were used. AgEcon Search, Google Scholar, Science Direct, Scopus, and Web of Science were the primary electronic search engines used to find pertinent studies for peer-reviewed research articles published in English. By looking through the reference sections of the gathered publications, pertinent research were also found. Additionally, customized searches were conducted with an emphasis on reports and research outputs from organizations that are actively involved in CSA. Sections of their website containing articles, material, or documents pertaining to CSA were then found and used in the review.

Criteria for including and excluding documents

Table 1: Criteria for including and excluding papers

Selection standards	Elimination Standards

English-language documents, including journal articles, book chapters, and reviews	Non-English-language documents files that are not book chapters, reviews, or journal articles.
Research centered on the agricultural region discusses CSA concepts (productivity, adaptability, and mitigation) and even the smallest AI approaches.	Research not concentrating on reports that do not include food insecurity, artificial intelligence, and CSA principles.

Data Sources

Scopus: A multidisciplinary abstract and citation database covering peer-reviewed literature across sciences and social sciences. JSTOR: A digital library providing access to academic journals and books with a strong emphasis on social sciences and economics. ScienceDirect: An extensive database of scientific and technical research articles, including a large collection of economics and agricultural studies. Google Scholar: A broad and inclusive search engine indexing scholarly articles, theses, books, and conference papers, useful for capturing grey literature and working papers.

Analytical Framework

Thematic synthesis of AI techniques, CSA pillars, and African contextual factors

Smallholder farmers in Africa are disproportionately affected by resource scarcity, weather extremes, and a lack of adaptive capacity, making their agricultural systems especially vulnerable to the effects of climate change. In response, a system known as Climate-Smart Agriculture (CSA) has emerged for improving resilience (adaptation), reducing greenhouse gas emissions (mitigation), and raising productivity in a sustainable way. At the same time, artificial intelligence (AI) is gaining popularity as a revolutionary tool for modernizing agriculture. This synthesis looks at how AI technologies match with the CSA pillars while accounting for Africa's socioeconomic, environmental, and infrastructure circumstances.

AI for Climate Risk Prediction and Adaptation

By providing advanced forecasting and early warning systems than conventional methods, artificial intelligences enable climate resilience. AI-powered weather models forecast the weather based on historical climate trends and satellite data. Due to their significant sensitivity to rainfall fluctuations, African farmers rely on region-specific forecasts from machine learning-based services like Google Earth Engine and IBM's The Weather Company (Makinde et al., 2023). Artificial intelligence (AI) is transforming climate risk prediction and response strategies in African agricultural systems. Drought models and weather forecasts are being improved through the use of big data analytics, satellite imagery, and machine learning algorithms. By simulating different climate scenarios, these technologies can provide early warning systems that are essential for predicting and lessening the effects of catastrophic weather events. For instance, convolutional neural networks and other AI-driven models have demonstrated exceptional predictive accuracy in identifying drought-prone regions and estimating rainfall variability across East Africa (Gebregiorgis et al., 2021). This ability reduces vulnerability and enables quick fixes, making farmers and politicians more prepared. AI-based drought modeling systems that use historical rainfall, soil moisture data, and meteorological variables to forecast drought duration and severity have been developed in places like East Africa. These technologies support risk management by helping smallholders plan planting and harvesting schedules more effectively (Nyakundi et al., 2021). AI integration, for instance, has improved anticipatory response planning and reduced agricultural losses in Kenya's National Drought Management Authority's early warning systems.

AI for Yield Optimization and Resource Efficiency

Artificial intelligence (AI) technologies have enormous potential to optimize yield by improving the precision and accuracy of agricultural performance forecasts. Using historical climate, soil, and crop data, predictive yield modeling projects agricultural output under a range of circumstances. For instance, Sub-Saharan Africa's maize and wheat yields have been predicted using Random Forest and Gradient Boosting algorithms, which incorporate farm management practices and climate variability (Jain et al., 2020). These projections help farmers and agricultural planners make informed decisions that can reduce risk and increase productivity. Zenvus, a business in Nigeria, forecasts yields and provides farmers with input recommendations by analyzing sensor data from farms using machine learning. By providing extremely precise predictive models that examine a variety of factors, including weather patterns, soil health indicators, past yields, and market dynamics, artificial intelligence is revolutionizing yield forecasting (Kamau et al., 2022). Artificial intelligence systems have also tremendously aided precise irrigation and nutrient application. In Kenyan horticultural farms, the use of artificial intelligence (AI) systems like SunCulture, which combine real-time data from IoT sensors and satellite imaging, has improved water use efficiency by more than 30% (FAO, 2021). The software determines the precise watering schedule by analyzing plant growth phases, rainfall patterns, and evapotranspiration, which minimizes waste and increases crop output.

AI for Pest, Disease, and Invasive Species Management

Predicting pest outbreaks is another application of AI. Machine learning models trained on weather, vegetation indices, and past pest trends are now used to forecast infestations of migratory pests, including the Fall Armyworm. These prediction techniques have reduced chemical use and minimized ecological harm in Tanzania by allowing customized pesticide applications (FAO, 2021). African agriculture is seriously threatened by pest and disease outbreaks, and artificial intelligence has emerged as a crucial tool for early detection and management. Farmers may snap images of leaves and diagnose diseases like cassava mosaic virus and maize catastrophic necrosis with over 90% accuracy by using mobile applications like PlantVillage Nuru, which use computer vision and machine learning (Hughes & Salathé, 2019). Farmers can now take measures before infestations spread thanks to this. Additionally, South Africa and Uganda are using drones with AI capabilities to survey fields and identify areas with high insect activity. These drones limit chemical exposure and save input costs by directing accurate pesticide spraying. The combination of AI and robotics is making Integrated Pest Management (IPM) a more sustainable and scalable alternative for CSA (Kamilaris et al., 2018).

AI in Agricultural Value Chains

Beyond production, AI increases efficiency across agricultural value chains. AI-driven logistics solutions accelerate delivery, minimize post-harvest losses, and optimize routes for transporting perishable goods. In Rwanda, AI has been used to coordinate crop collection in rural cooperatives, increasing the income stability of smallholders (CGIAR, 2022). Another use case is storage optimization. Artificial intelligence (AI) systems analyze temperature, humidity, and air quality data to provide real-time suggestions for changes to storage facilities. These technologies have been used by Senegal to preserve millet and maize in smart silos, significantly lowering the rate of spoiling (FAO & ITU, 2022). Additionally, blockchain technology and artificial intelligence have made it possible to track food supply networks. IBM's Food Trust platform, for instance, employs artificial intelligence (AI) to detect fraud and monitor quality and blockchain technology to provide unchangeable recordkeeping. Because it ensures manufacturers fair pricing and increases consumer transparency, this is a particularly important development for Africa's informal marketplaces (World Economic Forum, 2020).

3.0 Discussion

Pillar 1: Productivity

This pillar is most frequently translated into production quantification (even in the FAO definition). However, concentrating only on output overlooks two crucial pillar components: (1) Associating productivity with food security (and nutrition, one of its primary measures) is oversimplified. Increasing crop productivity can result in a decline in food security and even malnutrition, as demonstrated by a number of cases in the literature (Fraval et al., 2019). For instance, adopting a more productive crop may result in a drop in the variety of crops grown. Campbell et al. (2016) also point out that CSA should include other aspects of food security in addition to productivity. The sustainability of food security is the second important factor. The food security pillar's definition states clearly that increased productivity and food security raise the need for sustainability, but it offers no suggestions for how this should be measured. Sustainability can be characterized in a variety of ways. Although there are more than 100 definitions of sustainable agriculture (see, for example, Pretty et al., 2011), the general components of sustainable agriculture—which we concentrate on in this study—include the ability to produce desired outputs over longer time periods, such as decades, resilience (the capacity to absorb or recover from climate shocks and stresses), environmental friendliness with regard to regional resources, such as biodiversity, water, and soil, or globally, with regard to GHGs (Schiere et al., 2002; Pretty et al., 2011).

Such ideas of agricultural sustainability were almost intrinsically vague in the past, but there has been a recent upsurge in research on developing measures and indicators to make the general criteria applicable in a particular setting. Examples of this work include the Five Capitals (e.g., Karanja et al., 2016) and other multi-dimensional approaches such as the sustainable intensification (SI) evaluation framework, which examines five different dimensions (i.e., productivity, social, human, economics, and environment). As a result, we will investigate how production translates into food and nutrition security and go beyond the straightforward method of equating food security with output quantity to the biophysical and socioeconomic sustainability of production. Therefore, sustainability encompasses a wide range of elements that are also present in the other pillars, underscoring the challenge of merely dividing the CSA "cake" into three distinct pillars. Naturally, important traits like "resilience," which are specifically addressed in the "adaptation" pillar, will remain there and not be addressed in the "productivity" pillar. However, from our point of view, ecosystem services and environmental footprints do belong under the productivity pillar rather than mitigation. It is evident, though, that various people may have different ideas on how to precisely distinguish the three pillars.

Pillar 2: Adaptation

Wiederkehr et al.'s (2018) recent review provides a great summary of the current state of the art in assessments of climate change adaptation. One of their main findings is that the phrases "coping" and "adaptation" are frequently used interchangeably, making it difficult to define the idea of adaptation in many studies. In order to evaluate the frameworks' ability to manage both, we will take into account "short term adaptation," which reflects coping mechanisms, such as handling one-year weather anomalies or price volatility, as well as pertinent dangers. We will also look at "long term adaptation" to the progressively shifting climate, such as utilizing alternative crop varieties, cropping techniques, or management. Wiederkehr et al. (2018) make the important suggestion that in order to make significant and broadly applicable conclusions on climate change adaptation and possible technology adoption, the comparability of many local case study results needs to be addressed. "Ethnic background, economic status of households, e.g., farm size or number of livestock, and number of household members, are known to be important factors influencing the coping and adaptation behavior of households" (citation from Wiederkehr et al., 2018) and are not only relevant for the adaptation pillar. Other basic socio-economic characteristics of the study population include the age mean/range and sex ratio of the interviewees. Therefore, gathering this data from all research and creating a reliable "adoption indicator" are crucial. This section of the evaluation will determine whether the assessment frameworks distinguish across technologies, farms, and households in a way that influences their ability to adopt specific coping and adaptation strategies (referred to as "adoptability" in this context).

Pillar 3: Mitigation

Mitigation is a key pillar of CSA, and this pillar aims at reducing the environmental (climate) footprint of food production as

a) Globally, agriculture is the primary cause of environmental deterioration.

b) An important source of anthropogenic GHGs, particularly in LMICs, is agriculture.

c) Numerous ecological services, such as the storage of carbon and biodiversity, can benefit from agriculture.

Although GHG emissions are frequently used to quantify or assess mitigation, we would like to emphasize in this study that the line may be drawn more widely to encompass other environmental indicators, such as biodiversity, water use and quality, and nutrient use and leakage. However, in accordance with the convention, we will talk about these additional environmental mitigation indicators under the food security sustainability aspect, with an exclusive focus on GHG emission reduction in this pillar. It should be noted that, for instance, both short- and long-term GHG emissions are impacted by nutrient utilization efficiency (a crucial component of applying mineral fertilizer). Emission factors are a reasonable place to start when measuring greenhouse gas (GHG) emissions from agricultural sources (IPCC Guidelines to National Greenhouse Gas Inventories 2019). It is simple to quantify the mitigation effects of various management practices for the main greenhouse gases (GHGs) linked to agricultural output, such as CO2, CH4, N2O, and short-lived climatic pollutants. These are transformed into CO2-equivalents so that they can be compared to emissions from other sectors and natural sources. This is often carried out for a specific year and marks a particular moment in time. At the same time, ongoing monitoring will make it possible to identify variations in emissions as well as other changes over time (extremes, etc.), such as those brought on by local land use changes combined with climate change. In the context of measuring, reporting, and verification (MRV) at the national, regional, and international levels, these observations are crucial bookkeeping tasks. In particular, if mitigation activities are to be monetized—that is, if pollution is to be penalized—an MRV is required. MRVs are used to monitor changes in emissions and serve as the foundation for allocating climate subsidies to households that must deal with climate stress, which may become available through donations from governments like the OECD. Although the latter is still a long way off, the notion is that mitigation accomplishments may now be accurately assessed in addition to being detected. Given the large differences in management intensity, climates, soils, and even animal breeds, recent work attempts to improve the generic IPCC emission factors. This is because the majority of these estimates were developed for systems in developed countries and are probably not transferable to low and middle income countries (e.g., Pelster et al., 2017; Goopy et al., 2018; Ndung'u et al., 2018; Richards et al., 2018; Zhu et al., 2018, 2020). At the moment, each agricultural technique and technology must be evaluated similarly in order to satisfy pillars 1 and 2 requirements at the same time. Boundary definition is a crucial element that isn't covered in full here. What factors are used in these farm-level evaluations? The farm gate is typically regarded as the boundary, ignoring emissions from food waste, processing, and transportation. It is imperative that the assessment framework have such a defined boundary.

Challenges to CSA in Africa:, Limited Availability of Labor, Inadequate Farm Inputs and Materials, and Limited Credit and Finance

Limited Availability of Labor

One of the main factors influencing choices in the majority of smallholder production systems is the availability of farm labor. Demand for labor is typically higher than availability, at least seasonally, in many parts of Africa. Due to under nutrition and malnutrition, the prevalence of HIV/AIDS and other diseases, and rural-urban migration (particularly among young males), labor is frequently in short supply. Dependency ratios, or the proportion of people who are not employed to those who are, are exacerbated by illness and poor health and are higher in Africa than in any other part of the world (Radeksz, 2010). Deep-digging is necessary for CSA in some agro-ecological zones in order to break through soil crusts. This is a labor-intensive process that could raise the initial labor needs for site preparation (Milder et al., 2011). However, in other zones, because CSA does not require whole-field plowing or tillage, soil preparation takes less work than conventional agriculture. The direction and amplitude of these differences are also influenced by the kind of soil. Women may have higher labor needs even when overall labor is lower under CSA, or vice versa. Although this isn't always the case, Milder et al. (2011) noted that over time, CSA frequently lowers the amount of labor needed for farming when compared to conventional practice CSA frequently calls for more work in the short term, particularly for weeding and land preparation. Although tillage is an effective method of controlling weeds, if herbicides are not utilized, weeding may need significant initial labor increases when tillage is removed. Increased CSA yields during harvest can potentially result in unexpected labor peaks. However, depending on the crop, agro-ecological setting, years since adoption, and kind of farming system previously used, the labor implications of CSA are highly context-specific (Milder et al., 2011).

Inadequate Farm Inputs and Materials

The use of CSA in a maximally effective way is limited by limited access to and affordability of seeds, inorganic fertilizers, insecticides, and herbicides (Milder et al., 2011). However, in situations when agrochemicals are unavailable or too expensive, CSA can boost yields by promoting biological processes and management techniques that improve soil fertility and control weeds and pests. The majority of CSA systems require nitrogen-fixing plants, which can be trees like Faidherbiaalbida, shrubs, or annual herbaceous plants like legumes. By minimizing weed and insect issues, intercropping with these species enhances yields, soil health, and soil chemical and biological characteristics (Akinnifesi et al., 2010). Notwithstanding these advantages, farmers are unlikely to grow cover or other crops merely to improve soil fertility; instead, the plants must provide a direct benefit, like food for humans or animal feed (Baudron et al., 2009). Another significant obstacle to the adoption of CSA is the lack of access to high-yielding seeds and breeds. CSA frequently calls for specific seeds for intercrops or cover crops, which might be more challenging to find if they are species that have not historically been cultivated nearby (Milder et al., 2011). The implementation of CSA will continue to be hampered by input obstacles unless effective and trustworthy input supply chains are built.

Limited Credit and Finance

Lack of funds to invest in land, equipment, labor, seeds, breeds, and other farm inputs frequently prevents smallholder farmers from implementing CSA techniques. According to Milder et al. (2011), CSA is typically more profitable over the long run than conventional farming; but, realizing these long-term advantages necessitates an initial investment that is sometimes too costly or hazardous for small farmers to do on their own. Concerns about household food security make vulnerable farmers particularly risk cautious, and there isn't much margin for error. Furthermore, although CSA improves many farmers in the first year, others do not see higher yields or profitability for three to seven years (Hobbs, 2007). Farmers occasionally decide to stop participating in CSA during this time. Accordingly, when CSA offers notable advantages in the first or second year, long-term adoption is more likely (Reij et al., 2009). Promoting CSA in combination with improved seeds, appropriate agronomic methods, and occasionally inorganic fertilizers increases the likelihood of this instant impact (Milder et al., 2011). The implementation of CSA by smallholder farmers is significantly hampered by their inability or insufficiency to pay for farm inputs.

CSA Technologies and Practices in Use

Conservation agriculture, Agroforestry, Drought-resistant Crops

Africa is adopting the core CSA practices of drought-resistant crops, agroforestry, and conservation agriculture (CA) to boost agricultural production and resilience. It has been demonstrated that conservation agriculture, which includes permanent organic soil cover, minimal soil disturbance, and crop diversification through intercropping or rotation, improves soil health, increases water retention, and decreases erosion, especially in arid regions such as southern and eastern Africa (Kassam et al., 2019). By preserving the organic matter and soil structure, CA not only boosts output but also slows down global warming by storing carbon in the soil. Smallholders that use CA have shown increased yields and reduced susceptibility to climate shocks in a number of experimental programs in Zambia, Kenya, and Zimbabwe.

Agroforestry, which integrates trees into farming systems and offers significant socioeconomic and environmental benefits, is another crucial CSA tactic. The trees reduce land degradation, improve biodiversity, and provide shade, stabilizing microclimates for livestock and crops. In regions like the Sahel, farmer-managed natural regeneration (FMNR) has improved crop yields, restored damaged lands, and increased household incomes by collecting tree products (Mbow et al., 2014). In addition to these strategies, farmers have been able to maintain harvests despite more erratic rainfall by employing drought-resistant crops, such as enhanced millet, sorghum, and maize varieties developed through programs like Drought Tolerant Maize for Africa (DTMA) (Hellin et al., 2020). Because these crops are adapted to withstand water stress and shorter growing seasons, they are crucial for preserving food security in vulnerable locations.

Decision-support Systems and Early warning Mechanisms

Crucial components of CSA implementation are early warning systems and decision-support systems (DSS), which provide real-time data to guide farmer decision-making and mitigate the effects of climatic variability. These systems use satellite imagery, historical climate data, and predictive modeling to provide information on soil conditions, pest outbreaks, and weather patterns. For instance, by offering thorough data on biomass production and evapotranspiration across Africa, the FAO's WaPOR (Water Productivity through Open-access Remotely sensed derived data) platform aids in irrigation planning and water resource management (FAO, 2020). Early warning systems complement DSS by enabling governments and communities to respond to climate shocks before they become disasters. One such tool is the Africa RiskView platform, developed by the African Risk Capacity (ARC), which combines vulnerability data and drought projections to estimate the potential effects of food shortages and start contingency planning (ARC, 2023). In Ethiopia and Kenya, early warning data is used to activate safety nets and send cash transfers or agricultural supplies during periods of climate stress. These solutions have demonstrated potential in reducing losses and recovery times. Additionally, mobile-based advising systems such as Ethiopia's Sasakawa Africa services and Kenya's Digital Green are providing smallholder farmers with fast, localized weather forecasts, agronomic advise, and market information (Gebrehanna et al., 2021). Despite the revolutionary potential of these tools, their effectiveness is primarily reliant on farmers' digital literacy, internet connectivity, and local infrastructure.

Barriers to Adoption: Cost, Knowledge, Access

Despite the benefits of CSA technologies, their broad use in African contexts is hindered by a number of institutional, technological, and socioeconomic barriers. One major barrier is the inability to secure funding. Many smallholder farmers find it difficult to invest in improved crops, irrigation systems, or soil health treatments because of their limited financial resources. The absence of financing and insurance options tailored to the agricultural sector exacerbates this issue. Additionally, insecure land ownership discourages long-term investments in CSA practices like agroforestry and soil conservation (Branca et al., 2011). Without assured land ownership, farmers are reluctant to invest in technologies that may not yield immediate benefits or grow trees. The lack of technical knowledge and awareness of CSA practices is another major obstacle. Many rural populations may be wary of new tactics because they are used to conventional farming methods that have been passed down through the years. Weak agricultural extension systems that are frequently inexperienced and underfunded increase this. Language hurdles, low literacy rates, and inadequate digital infrastructure make it difficult to use mobile advisory platforms and decision-support tools effectively in places where CSA is advocated. Gender dynamics and cultural norms are also important; women, who make up a significant portion of Africa's agricultural workforce, frequently have limited access to land, credit, and training, which limits their ability to adopt new technology (Mwongera et al., 2017). To overcome these obstacles, a comprehensive and systematic strategy will be needed, one that includes public-private partnerships to increase access to CSA knowledge and resources, gender-sensitive policies, targeted subsidies or incentives, and investments in rural infrastructure.

AI Techniques and Global Agricultural Applications

Machine Learning

ML and DL are the primary subgroups of AI (Aceto et al., 2019). ML, a subfield of artificial intelligence, allows machines to learn from past experiences and provide predictions that are more accurate (Soori et al., 2023). To improve performance, it employs several algorithms or the same approach repeatedly. By learning from problem-specific training data, machine learning (ML) enables computer systems to perform tasks like object detection and natural language translation more effectively (Sreekanth et al., 2019). Without the need of explicit programming, machine learning algorithms can uncover intricate patterns and hidden insights (Jani et al., 2019). ML uses past calculations and patterns found in massive databases to make conclusions that are dependable and predictable. AI is implemented using specialized machines or systems that use machine learning technologies. Through direct training with data, machine learning (ML) involves identifying patterns and traits within the machine. Computers learn from specific data that people offer, and during the learning process, they make assessments and predictions based on the knowledge they have learned (Parekh et al., 2020). Supervised learning, unsupervised learning, and reinforcement learning are the three main learning approaches that make up machine learning. In supervised learning, the learning algorithm is given both the data and the associated labels, or responses. Making it possible for algorithms to learn from labeled data and generate precise predictions for unlabeled data is the aim of machine learning. Regression analysis, probability estimation, and object recognition are just a few of the activities that commonly use this method (Grinblat et al., 2016). Unsupervised learning, on the other hand, uses learning algorithms to find innate patterns, traits, and classes in unlabeled data. For tasks like dimensionality reduction, feature extraction, and clustering, this kind of learning is especially helpful. In order to optimize rewards or compensations based on available behaviors, an agent must interact with an environment, perceive its current state, and choose actions or action sequences. This is the final step in reinforcement learning. This kind of learning is frequently used in domains such as gaming and robotics. Depending on the particular issue and the data at hand, each of these learning techniques is applied in a different way.

Deep Learning

DL is a subfield of machine learning that makes use of CNNs or DCNNs. Deep neural networks, in contrast to simple neural networks, have hierarchical structures with numerous hidden layers. Additionally, they employ sophisticated neurons and techniques like multiple activations in a single neuron or convolutions. According to Filipi et al. (2019), these characteristics enable deep neural networks to process unprocessed input data and automatically determine the representations needed for the particular learning task. The primary difference between ML and DL is seen in the methods they use. Typically, machine learning research entails applying the researcher's experience or subject expertise to extract important features from the data. These features are used for further classification or regression analysis after being extracted manually or by image processing algorithms (Dadashzadeh et al., 2020). On the other hand, the DL algorithm does classification and regression training without the requirement for explicit feature engineering by automatically extracting features from raw picture data.

Remote Sensing

Technologies for remote sensing offer an analytical capacity that serves as an early warning system, enabling agricultural stakeholders to act quickly to address possible problems before they worsen and reduce crop production. The agricultural industry now has a variety of remote sensing alternatives thanks to recent developments in sensor technology, data management, and analytics. However, a lack of knowledge about these technologies' efficacy, appropriateness, and economic feasibility has prevented their full implementation. Remote sensing technologies provide an analytical capability that functions as an early warning system, allowing agricultural stakeholders to take prompt action to solve potential issues before they worsen and lower crop yields. Recent advancements in sensor technology, data management, and analytics have given the agricultural sector a wide range of remote sensing options. But their broad adoption has been hampered by a lack of understanding regarding the suitability, effectiveness, and economic viability of these technologies.

Robots

The introduction of agricultural robots signals an evolution in cultivation techniques and a revolutionary period in traditional farming (Lagnelöv et al., 2021). Through their seamless integration of robotics into the agricultural landscape, this state-of-the-art equipment have become innovation catalysts, transforming long-standing processes. These robots serve as technological sentinels, bringing in previously unheard-of levels of efficiency, accuracy, and sustainability in their quest to address the numerous issues facing the agriculture industry. A major component of this agricultural revolution, automation is crucial to addressing the many issues facing the industry (Del Cerro et al., 2021). Automation is the key to solving labor shortages and resource inefficiencies, and it has the potential to revolutionize farming methods (Oliviera et al., 2021). Beginning with the early introduction of basic robotic technologies like remote-controlled tractors and harvesters in the 1960s, the timeline history of agriculture robots offers a chronological overview of the integration of robotics in agriculture, outlining significant developments from the 1960s to the present and beyond (Tudor et al., 2022).

Table 2: Various Advantages of Climate-smart Agriculture Techniques for Enhancing Agricultural Productivity

Climate smart agriculture technique	Benefit	References
Crop diversification, residue management, zero-tillage, and crop establishment	enhance soil organic carbon pools, biological characteristics, and crop yields	(Jat et al., 2019)
Machine learning (Ml) algorithms	increase efficiency by precisely predicting the amounts of water, fertilizer, and pesticides required	(Kanuru et al., 2021; Puspaningrum et al., 2022; tanaka et al., 2024)
Artificial intelligence (AI)	improves the control of pests and diseases by early identification, observation, and control	(Kariyanna & Sowjanya, 2024)

Artificial intelligence of things (AIot)	Protecting crops from pest and disease dangers	(Blanco-Carmona et al., 2023; C.-J. Chen et al., 2020; Muhammed et al., 2024)
Robots and drones, Ml and soil water sensing methods	Maximize the use of herbicides and pesticides, cutting down on chemical use and lowering crop harm	(Indu et al., 2022; talaviya et al., 2020)
Remote sensing and satellite	Accurate monitoring of parameters like soil moisture, nutrient levels, and pest activity	(Babaeian et al., 2019; Kumari et al., 2023; Mu et al., 2022)

Global Case Studies and Insights

AI in North-America, Europe, and Asia

Climate-Smart Agriculture (CSA) practices have been widely implemented across North America, especially in the US and Canada, with the support of strong research institutions and governmental laws. Precision agriculture technology, which uses GPS, drones, and sensor networks to optimize inputs like water, fertilizer, and pesticides, is one well-known example. In the U.S. Corn Belt, these techniques have significantly improved crop efficiency while lowering greenhouse gas emissions (Schimmelpfennig, 2016). Large farms have also embraced cover crops and conservation tillage, which help to enhance soil health and sequester carbon. Farmers can now more easily learn about and adopt climate-resilient practices because to USDA's Climate Hubs and other public-private collaborations (USDA, 2020). In Europe, CSA has been incorporated into sustainable agriculture frameworks, particularly through the European Green Deal and the Common Agricultural Policy (CAP). Several countries, including Germany, France, and the Netherlands, have made large investments in agro-ecological advances, such as integrated pest control, organic farming, and agroforestry systems. For example, France's "4 per 1000" initiative seeks to increase soil organic carbon by 0.4% annually as a climate mitigation strategy (Minasny et al., 2017). Precision livestock farming, which makes use of smart collars and AI-based health monitoring, has also gained appeal as a way to reduce methane emissions and improve animal welfare. These innovations are supported by robust legislative incentives, data infrastructure, and subsidies that encourage the long-term transformation of agricultural systems. The use of CSA to solve the twin problems of food security and climate resilience is rapidly growing throughout Asia, particularly in China and India. The National Innovations in Climate Resilient Agriculture (NICRA) initiative in India has promoted drought-tolerant rice and pulse varieties, zero tillage, and weather-based agro-advisories (Venkateswarlu et al., 2011). Similarly, China has adopted digital agriculture platforms powered by artificial intelligence and big data to improve irrigation efficiency, pest control, and production forecasting. For instance, Alibaba's ET Agricultural Brain uses AI to give farmers advice on planting and disease control, which significantly boosts productivity and water efficiency (Xiong et al., 2020). These efforts are supported by robust institutional frameworks, large public investments in rural digital infrastructure, and national policy support.

Lessons for Scalability and Contextualization in Africa

The success of CSA in North America, Europe, and Asia offers valuable lessons for scaling in African contexts. First, funding research and digital infrastructure is essential. Precision farming and AI-driven systems have demonstrated potential in boosting resource efficiency and climate resilience, despite their high technology cost. This suggests that Africa needs to increase access to digital technology and build regional capacities for agricultural data analytics. Through partnerships with commercial tech companies and development organizations, smallholder farmers can benefit from low-cost, context-specific digital platforms. Using mobile technology, as is the case in Asia, could help spread localized climatic information, much like India's Krishi Vigyan Kendras (agricultural advising centers), which integrate ICTs into extension activities (Venkateswarlu et al., 2011). In addition, encouraging CSA implementation at scale requires institutional and policy congruence. The integration of climate-smart techniques into conventional agriculture can be accelerated by subsidies, carbon incentives, and sustainability targets, as demonstrated by the European experience. The key to promoting long-term investment in CSA in Africa will be creating supportive conditions through carbon credit regimes, inclusive agriculture subsidies, and land tenure reforms. Climate-smart towns and community-based innovation platforms are examples of adaptive learning systems that can guarantee local testing and customization of technologies. To address adoption obstacles specific to the African setting, it is also required to strengthen agricultural extension institutions, enhance market accessibility, and promote inclusive financing methods (Thornton et al., 2018).

AI Applications for CSA in Africa

AI for Climate Risk and Adaptation

Adaptation is quickly becoming a vital strategy to protect ecosystems and communities from the effects of climate variability, which poses unforeseen and difficult-to-predict difficulties. Because it requires controlling numerous interrelated aspects and the solutions are frequently not risk-informed for local measures, climate change adaptation has delayed. It presents fresh opportunities to close this crucial gap. It is an essential tool for connecting complicated global climate analyses with local adaptation strategies, and it can handle complex risk evaluations, even in locations with limited data. The strength of AI resides in its capacity to swiftly and precisely process and forecast effects from enormous volumes of data. The World Meteorological Organization emphasizes that artificial intelligence (AI) is improving the precision and speed of weather forecasts by bringing new technologies to earth system prediction. AI is being used by Google and Microsoft to improve human health, wildfire tracking, and flood predictions. Although many of these models frequently perform better than conventional forecasting methods, they have not yet been made practical for use in underdeveloped nations. Therefore, at ESCAP, programs such as the Asia Pacific Risk and Resilience Portal are utilizing predictive AI to enhance multi-hazard-multi-criteria risk modeling by identifying vulnerable areas in developing nations using open-source datasets on climate, hazards, socioeconomic factors, and the environment. The Portal's risk analytics were used to train disaster management policymakers in Bhutan, where mountainous terrain and a lack of data present major obstacles, to create impact scenarios for sectors that are sensitive to climate change. In the same manner, the Portal helped small island developing states like Eswatini get ready for the long-term effects of sea level rise and other coastal dangers. For these nations, where a lack of data has historically made it difficult to conduct effective climate and disaster analysis and planning, AI-powered solutions are essential (UN-ESCAP, 2024).

Weather Forecasting, Drought and Flood Prediction

Nairobi, to improve the accuracy of extreme weather forecasts at a reasonable cost, climate scientists in East Africa are integrating artificial intelligence (AI) into traditional weather forecasting methods. Climate change is making extreme weather events more frequent and intense in places like the southern region of the continent, where previous devastating floods occurred after the worst drought in decades (Obed, 2024). Researchers say they have created a first-of-its-kind hybrid modeling approach to provide more accurate rainfall forecasts without the need for costly supercomputers by fusing AI with physical atmospheric processes employed in traditional forecasting. Shruti Nath, a climate scientist and researcher at Oxford University's physics department, says, "We start with the traditional forecasts and add the AI model over it to correct what was not captured so that it better represents observed data." In an area where precise observational data is frequently sparse, she claims that this model, which only needs a laptop to operate, provides local meteorological organizations with an inexpensive means of producing more accurate forecasts. Ethiopia and Kenya are presently implementing the model. Researchers intend to duplicate it in other regions of the world dealing with comparable issues if it proves effective in East Africa. According to the researchers, the project has the potential to transform East African weather forecasting and early warning systems, increasing the region's resilience to climate change-related weather extremes including drought and floods.

AI for Yield Optimization and Resource Efficiency

AI’s role in agriculture extends beyond crop management to the efficient allocation of resources and sustainability. By leveraging AI-powered data analysis, farmers can make more precise decisions about resource allocation, such as water, fertilizers, and pesticides. This not only reduces resource waste but also minimizes the environmental impact associated with agricultural runoff (Siddiqui et al., 2023). The AI-driven precision agriculture tailors farming practices to individual crops and field conditions, optimizing resource usage. Water is a precious resource in agriculture, and AI plays a significant role in its responsible management. AI-driven systems can monitor soil moisture levels and weather conditions in real time. By combining these data sources with predictive analytics, AI can provide irrigation recommendations that are not only specific to the crop but also responsive to changing weather patterns. This level of precision ensures that water is used efficiently, minimizing water wastage and preventing over-irrigation, which can lead to soil degradation and water runoff. In regions facing water scarcity, AI-powered water management is indispensable for ensuring sustainable agriculture. Efficient nutrient management is critical for crop health and environmental sustainability. AI systems can analyze data related to soil quality, crop nutrient requirements, and the composition of fertilizers (Kumar et al., 2024). With this information, AI can optimize the application of fertilizers, ensuring that crops receive the nutrients they need while reducing excess application that can lead to nutrient runoff into water bodies, causing environmental harm. AI-driven nutrient management benefits both crop yields and environmental conservation. Pest and disease control are pivotal aspects of sustainable agriculture. AI-equipped monitoring systems can detect early signs of pest infestations and diseases, often before they are visible to the human eye. By alerting farmers to these issues, AI enables timely interventions. AI can provide recommendations for targeted pesticide application, minimizing the use of chemicals while effectively addressing the problem.

Predictive Analytics for Crop Yield Optimization

The combination of technology and predictive analytics has resulted in a significant change in the productive domains of contemporary agriculture (Alazzai et al., 2024). The field of predictive analytics for crop yield optimization is explored in this chapter, along with the critical role of machine learning algorithms, the variety of data sources and sensors that drive this revolution, and the advanced crop yield prediction models that have completely changed farming's future.

Table 3: Predictive Analytics for Crop Yield Optimization

Method of Predictive Analytics	**Description**	**Application in Crop Yield Optimization**
Machine Learning Models	Predict future yields by using algorithms to examine weather trends, crop characteristics, and previous data.	Makes precise forecasts, spots trends, and assists farmers in making well-informed choices to maximize crop productivity. .
Weather Forecast Integration	Incorporates weather forecasting data into predictive models to assess the impact of climatic conditions on crop growth.	Enables proactive decision-making based on anticipated weather conditions, optimizing planting and harvesting schedules.

Remote Sensing and Satellite Imagery	Utilizes satellite and remote sensing data to monitor crop health, identify stress factors, and predict potential yield outcomes.	Provides real-time information on crop conditions, supports early detection of issues, and aids in yield forecasting.
IoT Sensors in Agriculture	Uses Internet of Things sensors to gather data in real time on temperature, soil moisture, and other variables influencing crop development, then incorporates the data into prediction models.	Enables continuous monitoring, enhances precision agriculture, and aids in predicting optimal conditions for crop growth.
Data Analytics for Pest and Disease Prediction	Integrates data on pest and disease incidence with predictive models to anticipate outbreaks and implement preventive measures.	Supports early pest and disease management, reducing crop losses and contributing to overall yield optimization.
Precision Irrigation Systems	Combines precision irrigation equipment with forecasting techniques to maximize water use according to projected crop water needs.	Improves water efficiency, minimizes over-irrigation or drought stress, and supports sustainable crop yield optimization.
Feedback Loops for Continuous Improvement	Establishes feedback mechanisms to continuously update predictive models based on actual field performance and outcomes.	Enables adaptive management, improves model accuracy over time, and supports continuous optimization of crop yield strategies

AI for Pest and Disease Management

By improving predictive analytics, automating detection procedures, and enabling integrated pest management (IPM), artificial intelligence has emerged as a significant force in crop security. Predictive analysis is one prominent use case, where AI forecasts possible infestations by analyzing past weather trends and pest behavior. For crops that are particularly at risk, this "early warning system" is especially helpful since it allows farmers to take action before insects proliferate. Furthermore, real-time pest monitoring is another area where artificial intelligence shines. AI-equipped drones and sensors reduce the need for pesticides by assisting farmers in identifying problems early on by differentiating between healthy and infested plants. By combining chemical and biological controls based on precise data, IPM with machine intelligence improves sustainability—a technique known as "less spray, more strategy."

Last but not least, "smart tech" uses include remote farm monitoring using devices like sensor-doubling pheromone traps. These innovative approaches are a step toward accurate, long-term pest management that will enable farmers to preserve yields while using fewer chemicals. In summary, AI turns pest management into an exacting art form rather than merely aiding in infestation control.

Mobile Platforms and Smallholder Integration

Using mobile phone farming applications improved the agricultural experience for smallholder farmers in a number of ways. They discovered that knowledge was now more easily, quickly, and affordably accessible. Texting someone to ask about a commodity's pricing or to connect with a buyer was reasonably priced. Farmers were also able to make judgments quickly because information was relayed quickly from texting to receiving a response. The farmers were able to make timely marketing decisions based on the market giving higher returns because the information was accurate and up to date. Through the usage of the applications, farmers were able to establish networks and connections with other farmers and traders. It's interesting to note that as the networks and linkages grew, they finally took over as the primary source of production information for farmers. In order to obtain the information they required, the farmers typically called other farmers. As a result, farmers were able to establish connections with other farmers who served as valuable information sources thanks to mobile phone farming applications. Kenyan mobile platform M-Farm uses web-based services and SMS to link farmers and buyers. For farmers, particularly those who grow rice, the website offers pricing comparisons, market data, and direct marketing options. Farmers can sell their produce directly to customers or big buyers, obtain fair market prices, and stay away from exploitative middlemen by using M-Farm. Smallholder farmers now have more negotiating power and easier access to markets thanks to M-Farm. For Kenyan rice farmers, more market prospects and income stability are the results of this platform's efficiency and transparency. Furthermore, the platform makes bulk selling easier, which raises prices and lessens logistical difficulties (Okello et al., 2012).

Early Detection Systems using Computer Vision and Machine Learning

Case Study: Soybean

In 2015, Dandawate et al. established automatic methods for detecting diseases in soybean crops, and in 2023, Kumar et al. Thus, they converted the RGB image into an HSV color space. Techniques based on color and clusters were used for division. The SIFT technique was used to determine the type of plant based on the structure of its leaves. Citrus illnesses were identified by Pydipati and colleagues (2006) using discriminant analysis and color texture features. They also employed the color co-occurrence method (CCM) to determine whether the sick leaves could be identified using hue saturation and intensity (HSI) color characteristics and statistical classification techniques. This approach achieved an accuracy of more than 0.95 (Pydipati et al., 2006). The following methods can be used to identify the involvement of these infections, which can infiltrate different plant sections such fruits, vegetables, stems, and more.

●Understanding and categorizing the illnesses

●recognizing the impacted area

●Getting the feature set for the impacted area

This method chooses the right light source and shooting angle while building the visual scheme using plant diseases and pests. This technique guarantees consistent illumination in photos. Although designed imaging systems can simplify the process of building a standard algorithm, they also raise the cost of deployment. Standard algorithms may not always be able to fully eliminate scene changes from recognized findings in a natural setting (Dell' Aquila 2009).

AI in Agricultural Value Chains

Artificial intelligence (AI) is revolutionizing global agriculture by increasing the sustainability, resilience, and efficiency of food supply systems (Grote et al., 2021; Songol et al., 2021). The definition of artificial intelligence (AI) is the ability of machines to simulate human intelligence processes. This encompasses machine learning, computer vision, natural language processing, and robotics. AI in agriculture holds promise for addressing systemic problems including food insecurity, supply chain fragmentation, and environmental degradation in addition to increasing productivity and efficiency. AI is transforming agricultural supply networks by offering innovative solutions to enduring problems with food insecurity, waste, and inefficiency. AI is used in logistics, predictive analytics, and crop monitoring to increase agricultural productivity, sustainability, and resilience. As countries like Nigeria look to modernize their agricultural sectors, lessons learned from the adoption of AI in developed economies like the US can provide a roadmap for using technology to improve food systems and achieve long-term development goals (Krishnan et al., 2020; Songol et al., 2021).

Barriers to AI Integration in CSA in Africa

Absence of Data Quality and Availability One of the main obstacles to the application of AI in agriculture is the scarcity of high-quality data (Jha et al., 2019). Large, high-quality datasets are necessary for AI systems to efficiently program algorithms. It is challenging and costly to gather agricultural data over wide geographic areas and seasons. Since agricultural production takes place outdoors in intricate natural systems, these data are extremely unpredictable and inconsistent due to factors like weather, soil conditions, crop genetics, and management approaches (Matthews et al. 2002). Farmers can gather high-resolution data on several parameters using precision agricultural techniques. But often, this information is not enough (Khanal et al., 2020). It's possible that important data like weather, fertilizer applications, watering schedules, and insect pressure won't be captured or connected to the sensor data. Programming AI models to generate precise predictions and suggestions is challenging in the absence of these data (Zhang et al., 2021). Data quality is further diminished by the variation in agricultural techniques. The consistency of data across farms is diminished if different producers employ disparate preventive strategies for the same illness. It is necessary to have similar concepts in order to align and integrate various datasets (Kumar et al., 2021). Still, worries about competitiveness, privacy, and proprietary techniques frequently make agricultural stakeholders reluctant to share data.

Barriers to Accessing High Technology

Many farmers struggle to access and use these cutting-edge technology, despite the fact that AI is essential for increasing agricultural output, sustainability, and efficiency (Balaska et al., 2023). For smallholder farmers in underdeveloped nations, AI software, hardware, and infrastructure are too expensive. The use of AI technologies, such as computer vision weeding or robotic harvesters, necessitates greater investment and experience, even for larger farms in developed nations (Kakani et al., 2020). AI usage in research initiatives and agriculture activities is also hindered by fundamental technological shortcomings. In distant locations, technological availability is limited by unreliable electricity, poor internet connectivity, malfunctioning sensors, and a lack of technical support (Bali et al., 2023; Philip and Williams 2019). The majority of AI applications today rely on big data analytics and cloud computing, which necessitate constant internet access. Real-time AI is impossible in barns and fields without connectivity. Even in the presence of infrastructure, farmers' lack of fundamental digital skills further hinders their use of technology (Dhillon and Moncur, 2023). If the training data does not represent various farms, AI algorithms are also hampered by data and societal prejudice. Smaller farms with fewer resources may be excluded or fail because the majority of agricultural AI produced currently uses data from large industrial farms (Sparrow et al., 2021). Gathering field data in a range of settings is necessary to create AI tools that are suited to smallholder farming systems. However, it has proved troublesome due to issues related to inadequate technology accessibility.

High Level of Input Cost

The high expenses associated with developing and implementing AI technologies in the agricultural sector provide significant challenges (Dwivedi et al., 2021). Both public researchers and private businesses find it costly to gather the vast datasets needed to train reliable AI models. It costs a lot of money up front to install feet of sensors on farms in order to collect millions of data points on factors like crop growth, soil chemistry, and weather patterns (Saiz-Rubio and Rovira-Más 2020). The costs related to labeling, processing, and data storage are also significant. The specialized equipment required to implement agricultural AI, such as autonomous tractors, camera-enabled robots, and aerial drones, is not inexpensive (Uzhinskiy 2023). In particular, smaller farms do not have the funds to buy high-tech solutions. The strain is further increased by maintenance expenses. Another difficulty is scaling expenses as operations grow. The talent needed to create and execute the intricate programming, analytics, and algorithms is expensive and in short supply (Philip Chen and Zhang 2014). Salaries are rising as other businesses compete with agriculture for highly qualified technical workers. Sustained high expenses are also a result of ongoing model updating and monitoring by trained staff (Aldoseri et al., 2023). Furthermore, monopolistic pricing is permitted and competition is discouraged by intellectual property rights on proprietary AI technologies. Large tech giants purchase startups that make breakthroughs, allowing them to charge higher costs for their AI solutions (Makridakis 2017). Agricultural laborers' lack of digital knowledge and accessibility is another obstacle (Soma and Nuckchady 2021). Introducing cutting-edge technologies necessitates a fundamental understanding of computers and technology. According to Shaw et al. (2006), training programs can aid in improving the usability and accessibility of AI systems for pertinent stakeholders. Concerns exist around ethical AI methods, transparency, and data privacy. Without knowing exactly how this information is being used, farmers are hesitant to embrace AI technologies (Kerr 2004). Strong cybersecurity safeguards, equitable, responsible AI algorithms, and transparent communication on data collection, processing, and storage are all necessary. Another difficulty is cultural attitudes and views. Generally speaking, the agriculture sector is antiquated and resistant to quickly evolving technologies. According to Rose et al. (2016), younger farmers seem to be more receptive to innovations than older ones. Over time, creating intuitive AI interfaces and implementing educational initiatives can help to progressively lessen unfavorable perceptions.

Strategies for Scalable and Inclusive AI-CSA Integration

Human-in-the-Loop AI Models

Particularly in complex changing contexts like agriculture, human-in-the-loop (HITL) AI models incorporate human knowledge into the AI decision-making process to guarantee relevance, accuracy, and reliability. HITL AI systems are becoming more and more crucial in the African environment for adjusting agricultural solutions to smallholder farmers' realities. To improve contextual knowledge and lessen algorithmic bias, these models integrate human judgment with machine learning algorithms at crucial points, like data categorization, model validation, and decision support (Amershi et al., 2014). In order to ensure that the models adjust to local pest kinds, climatic circumstances, and cropping patterns, image-based plant disease detection systems, for instance, can enlist the help of local agronomists and extension workers to validate AI diagnoses. Additionally, the human-in-the-loop method increases usefulness and confidence. AI tools that incorporate the knowledge, expertise, and preferences of farmers and agricultural consultants throughout design and iteration are more likely to be adopted. IBM's EZ-Farm initiative in Kenya supports crop health monitoring and precision irrigation in greenhouse farming by integrating IoT sensors with human feedback loops. The system improves recommendations over time by learning from both human judgments and machine inputs through repeated training (Agyeman et al., 2020). Similar to this, farmers can ask questions, get individualized advice, and submit fresh data through interactive voice response (IVR) systems that use AI-powered call centers. This enhances the model's ability to respond to local needs. In addition to enhancing AI system performance, HITL guarantees that farmers maintain control over the operation and development of the technology.

Integrating AI into African Policy and Agricultural Development Programs

To maximize AI's benefits in agriculture, policies must be integrated. While many countries link AI projects to their National Adaptation strategies (NAPs) or CSA strategies, few actually do. Ethiopia's Climate Resilient Green Economy Strategy, which incorporates digital tools and remote sensing into national planning, is a promising example (Gebru et al., 2022). When AI complies with such regulations, funding and institutional backing are assured. AI is a more appealing investment since it aligns with the Sustainable Development Goals (SDGs). Through targeted interventions, the use of AI to agriculture directly advances SDGs 2 (Zero Hunger), 13 (Climate Action), and 5 (Gender Equality). The UNDP (2020) claims that digital agriculture can accelerate Africa's progress toward accomplishing these goals provided it is coordinated across ministries. These initiatives must be accompanied by capacity-building. Governments should encourage researchers, policymakers, and extension agents to be AI literate. Affordability, inclusivity, and sustainability are the main focuses of national AI policies for agriculture that nations like Ghana and Rwanda have started to write (Makinde et al., 2023). Public-private partnerships that concentrate on training and digital infrastructure can support these initiatives.

Human-Centered Artificial Intelligence

In order to guarantee that AI is dependable, secure, and trustworthy, Human-Centered AI (HCAI) is a relatively new strategy that gives humans control over AI technology and aligns them with human values, ethical principles, and legal criteria (HCAI, 2022). The foundation of HCAI is the idea that technology should enhance human potential. According to HCAI, AI systems ought to be clear, understandable, and flexible enough to accommodate the needs of different users. The tenets of Explainable AI (XAI), which stress the significance of making AI judgments intelligible and interpretable to humans, align well with this. Users can find it difficult to trust or even employ AI technologies effectively in the absence of this clarification. These systems need to be designed with domain-specific knowledge and a thorough grasp of human behavior and cognition. A true "human-in-the-loop" methodology guarantees that AI systems are iteratively improved based on ongoing human feedback rather than being built in a vacuum. Error correction is only one aspect of this; another is bringing the system's functioning closer to human ideals and requirements. Such a strategy is essential to preventing AI from replacing human knowledge. Rather, AI is supposed to work alongside humans, boosting and complementing their abilities. Although there is now a lot of discussion about this, there isn't yet a single, widely recognized framework for HCAI. Nonetheless, there are broad ideas and approaches that serve as the cornerstone of what could develop into an HCAI framework. This is a summary founded on broad ideas and factors:

1) Human-Centered Design:

•Recognize and respond to user contexts and needs.

Engage users at every stage of the development process.

• Give user experience and user-friendly interfaces top priority.

2) Explainability & Transparency: AI should make its decision-making process transparent.

Employ Explainable AI (XAI) methods to enable the interpretation of algorithms.

• Ascertain that users can comprehend and have faith in AI results.

3) Empowerment & Augmentation: • Create AI that enhances human potential.

Why Human tasks should be supported by AI, not replaced.

• Give top priority to systems that foster human creativity.

4) Fairness & Ethical Considerations: • Give user privacy and data security top priority.

• Reduce and deal with AI model biases.

• Make sure AI solutions are fair.

5) Flexibility & Adaptability: AI should adjust to the needs of each user.

• Provide possibilities for customization.

AI models should be updated often in response to feedback.

6) Quality & Dependability: Make sure AI functions securely in every setting.

• Give resilience to hostile attacks first priority.

Put fail-safe measures in place.

7) Iteration and Continuous Learning: • Put in place systems that allow AI to develop.

• Adopt a "human-in-the-loop" strategy.

•Continually improve AI systems according to their results.

8) Teamwork & Multidisciplinary Method

• Integrate knowledge from cognitive science, artificial intelligence, and other fields.

• Encourage cooperation between domain and AI specialists.

• Encourage end users and developers to work together.

Open-source Solutions Versus Proprietary Tools

Frameworks, libraries, or models that have publicly accessible source code are referred to as open source.

Crop disease identification, supply chain optimization, weather forecasting, autonomous weeding robots, and precision planting are a few instances of open source AI in agriculture.

On the other hand, proprietary AI refers to models or software that are owned and managed by a company.

Examples are Crop Doctor, soil organic, and Blue River Technology's "See and Spray."

Cost analysis, privacy and security issues, performance and scalability, and innovation pace are some important considerations when deciding which kind of AI to employ.

Table 4: Table of cost factors

Cost Factor	Open Source AI	Proprietary AI
Initial cost	Free	High licensing fee
Maintenance	high because of internal needs	Included in vendor fees
Expertise	Skilled team required	Lower need for technical expertise
Long term cost	Savings due to no licensing fees	Recurring license costs

Future Pathways

Interdisciplinary Research

To tackle complicated issues, interdisciplinary research combines expertise from several disciplines. Cross-disciplinary cooperation is essential for future CSA research and development, combining expertise from the social sciences, computer sciences, agricultural sciences, environmental studies, and economics. More than just technical solutions are needed to address the complexity of food systems in Africa; socioeconomic, ecological, and technological dynamism must be understood. For instance, developing more pertinent decision-support systems can be facilitated by fusing agronomic knowledge with AI expertise. Conversely, social scientists play a critical role in creating culturally relevant treatments that are in line with the norms and values of the community. Furthermore, interdisciplinary cooperation encourages the joint development of novel models that capture the realities of Africa's smallholder agriculture. For instance, by incorporating risk perception into communication tactics, the integration of behavioral economics and climate science can enhance early warning systems. In a similar vein, collaboration between data scientists and local extension agents may guarantee that AI models are tested against local farming expertise and trained using high-quality, ground-truth data. In order to scale climate information services through integrated research frameworks, platforms like CGIAR's Accelerating Impacts of CGIAR Climate Research for Africa (AICCRA) bring together a variety of institutions (AICCRA, 2022). Enhancing these cooperative areas can lead to fair, demand-driven results in addition to innovative breakthroughs. AI computing is predicted to completely transform CSA in Africa. It is clear that farming with AI tools is a future that is already on the verge of happening since agricultural methods are rapidly changing into stage-dependent AI. In the near future, it is anticipated that cooperation between the public and community climates and private technological industries would increase. For long-term effects, many enterprises are making significant investments in technological and climate data innovation. Governments, especially in Africa, will invest heavily in developing infrastructure for AI technologies. It goes without saying that in order for AI activities to grow in a fair and sustainable manner, countries will need to invest in the following: ongoing energy infrastructure investment because AI uses a lot of energy; training and capacity building so that more communities and indigenous people can use such tools; and transportation infrastructure to swiftly distribute tools and hardware throughout Africa's remote areas. Furthermore, it is likely that frameworks for laws and policies will be updated or reinforced to incorporate AI technologies into social settings for long-term interactions.

4.0 Conclusion

By evaluating numerous research findings, this paper examines the body of literature currently available on the application of AI technology in climate-smart agriculture. Africa, a region grappling with the twin issues of food hunger and climate vulnerability, might benefit greatly from the advancement of Climate-Smart Agriculture (CSA) through the use of artificial intelligence (AI). AI has the potential to greatly improve environmental sustainability, resilience, and production through breakthroughs like intelligent decision-support platforms, early warning systems, and precision farming. AI technologies present a previously unheard-of chance to maximize resource use, anticipate climate-induced disruptions, and modify farming operations appropriately by facilitating real-time, data-driven decision-making. AI's incorporation into CSA signifies a paradigm shift toward smarter, more sustainable agri-food systems that can feed Africa's expanding population under climate pressure, not just a technical breakthrough. However, realizing this promise necessitates the use of inclusive and context-aware AI. Agro-ecological zones, cultural customs, and socioeconomic realities are all represented in the great diversity of African agricultural systems. AI solutions must therefore be tailored locally, based on participatory models, and directed by feedback systems led by farmers. Designing and implementing AI solutions with women, youth, and underrepresented communities at the forefront is crucial for impact and equity. Iterative learning procedures, co-designed platforms, and human-in-the-loop models will be essential for establishing relevance, usability, and trust. AI has the possibility of widening rather than reducing current disparities if local ownership and capability are ignored. In the future, strong ethical governance frameworks and scalable, multidisciplinary research agendas are desperately needed. Long-term capacity building, open innovation ecosystems, and cross-sectoral collaborations that balance the interests of the public, corporate, and community sectors should be the focus of investments. Policy frameworks need to protect data sovereignty, encourage algorithmic transparency, and guarantee that AI is used responsibly while adhering to environmental justice ideals. Technology alone won't drive CSA in Africa in the future; rather, it will depend on our combined capacity to match innovation with sustainability, ethics, and inclusivity. AI has the potential to be a key component of Africa's agricultural transformation amidst climate uncertainty by encouraging interdisciplinary cooperation and ethical stewardship.

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