

REVIEW

Challenges in Sub-Saharan Africa's Food Systems and the Potential Role of AI

Desafíos en los Sistemas Alimentarios de África Subsahariana y el Potencial Rol de la Inteligencia Artificial

Petros Chavula¹  , Fredrick Kayusi²  

¹World Agroforestry Centre, St. Eugene Office Park, Kabulonga, Lusaka, Zambia & Africa Centre of Excellence for Climate-Smart Agriculture and Biodiversity Conservation, Haramaya University. Dire Dawa, Ethiopia.

²Department of Environmental Studies, Geography & Planning, Maasai Mara University. Narok-Kenya.

Cite as: Chavula P, Kayusi F. Challenges in Sub-Saharan Africa's Food Systems and the Potential Role of AI. LatIA. 2025; 3:318. <https://doi.org/10.62486/latia2025318>

Submitted: 09-01-2024

Revised: 15-07-2024

Accepted: 13-05-2025

Published: 14-05-2025

Editor: PhD. Rubén González Vallejo 

Corresponding Author: Petros Chavula 

ABSTRACT

Sub-Saharan Africa (SSA) faces persistent food insecurity due to low agricultural productivity, limited access to modern technologies, and growing climate variability. This study explores the transformative potential of Artificial Intelligence (AI) to enhance food systems across SSA. The objective is to assess how AI applications—such as machine learning, remote sensing, and big data analytics—can address systemic inefficiencies in cereal crop production, with a focus on barley, millet, and sorghum. Using a systematic review approach aligned with PRISMA guidelines, literature from 2015-2025 was analyzed across multiple databases to identify empirical studies and models related to AI in SSA agriculture. Results reveal that AI can significantly improve crop monitoring, yield forecasting, and resource optimization. However, adoption barriers such as inadequate infrastructure, financial constraints, and the digital divide persist. The study concludes that while AI holds significant promise, its success in SSA depends on inclusive policies, capacity building, and localized data governance. It recommends interdisciplinary research, investment in rural digital infrastructure, and participatory innovation frameworks to empower smallholder farmers and ensure equitable AI deployment. This review provides a roadmap for integrating AI into SSA food systems to enhance resilience, productivity, and food security.

Keywords: Agriculture; Artificial Intelligence; Food Systems; Machine Learning; Sub-Saharan Africa; Sustainability.

RESUMEN

África Subsahariana (ASS) enfrenta una inseguridad alimentaria persistente debido a la baja productividad agrícola, el acceso limitado a tecnologías modernas y la creciente variabilidad climática. Este estudio explora el potencial transformador de la Inteligencia Artificial (IA) para mejorar los sistemas alimentarios en la región. El objetivo es evaluar cómo las aplicaciones de IA—como el aprendizaje automático, la teledetección y el análisis de macrodatos—pueden abordar las ineficiencias sistémicas en la producción de cultivos de cereales, con un enfoque en la cebada, el mijo y el sorgo. Utilizando un enfoque de revisión sistemática alineado con las directrices PRISMA, se analizó la literatura publicada entre 2015 y 2025 en múltiples bases de datos para identificar estudios empíricos y modelos relacionados con la IA en la agricultura de ASS. Los resultados revelan que la IA puede mejorar significativamente el monitoreo de cultivos, la predicción de rendimientos y la optimización de recursos. Sin embargo, persisten barreras de adopción como la infraestructura inadecuada, las limitaciones financieras y la brecha digital. El estudio concluye que, aunque la IA ofrece un gran potencial,

su éxito en ASS depende de políticas inclusivas, desarrollo de capacidades y una gobernanza de datos localizada. Se recomienda fomentar la investigación interdisciplinaria, invertir en infraestructura digital rural y promover marcos de innovación participativa para empoderar a los pequeños agricultores y garantizar una implementación equitativa de la IA. Esta revisión ofrece una hoja de ruta para integrar la IA en los sistemas alimentarios de ASS y mejorar su resiliencia, productividad y seguridad alimentaria.

Palabras clave: Agricultura; África Subsahariana; Aprendizaje Automático; Inteligencia Artificial; Sistemas Alimentarios; Sostenibilidad.

INTRODUCTION

Sub-Saharan Africa (SSA) faces chronic food insecurity, where demand often exceeds supply, leaving marginalized populations vulnerable to hunger.^(1,2,3) Despite being rich in natural resources, SSA nations rank low on the Human Development Index, with agriculture, although central to the economy, remaining largely subsistence based. Contributing factors include limited access to finance, markets, and technology; low education levels; outdated farming practices; and significant climate variability, which results in unstable yields.^(1,2,3)

Agriculture employs 65-80% of the workforce and contributes about a third of the region's GDP, yet productivity remains among the lowest globally. Numerous development projects have aimed to support farmers, but challenges persist, such as inequitable land distribution, limited project funding, weak extension services, and poor post-project sustainability.^(1,2,3,4) Scheme and project farmers alike struggle due to insufficient resources and support. Artificial Intelligence (AI) presents a promising opportunity to transform SSA's food systems by improving access to real-time data, enhancing decision-making, increasing yield forecasting accuracy, and optimizing resource use.^(4,5,6,7,8)

By addressing systemic inefficiencies and improving the scalability of agricultural interventions, AI can play a pivotal role in building more resilient and productive food systems across the region. Sub-Saharan Africa (SSA) faces persistent food insecurity, driven by low agricultural productivity, limited access to markets and technology, and increasing climate variability. Despite agriculture employing up to 80 % of the population and contributing significantly to GDP, most farming remains subsistence-based and inefficient.^(5,6,7,8,9,10,11,12)

Development initiatives often fall short due to inadequate funding, poor land governance, and weak extension services. In this context, Artificial Intelligence (AI) offers transformative potential to address these systemic challenges by enhancing decision-making, improving resource use, and increasing yield reliability. This paper explores how AI can be effectively integrated into SSA food systems to support sustainable agricultural development and food security.

METHOD

This review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, ensuring a rigorous and transparent methodological framework for assessing the role of Artificial Intelligence (AI) in Sub-Saharan Africa's food systems.

Research Design

This systematic review applies PRISMA guidelines to evaluate how Artificial Intelligence (AI) technologies are utilized to enhance various dimensions of food systems in Sub-Saharan Africa, with particular attention to cereal crops such as barley, millet, and sorghum. The review assesses AI applications in areas including crop monitoring, yield prediction, climate-smart agriculture, supply chain optimization, and environmental impact analysis using tools like machine learning, remote sensing, and predictive modeling. Given the emerging nature of this research area, the review includes both AI-exclusive studies and those integrating AI with traditional approaches like Life Cycle Assessment (LCA) to broaden the understanding of its transformative potential in regional agriculture.

Data Collection Strategy

A comprehensive and structured search was conducted across Scopus, Web of Science, and Google Scholar databases. Search terms combined keywords related to AI applications and Sub-Saharan food systems: ("Artificial Intelligence" OR "Machine Learning" OR "AI") AND ("Food Systems" OR "Agriculture") AND ("Sub-Saharan Africa") AND ("Barley" OR "Millet" OR "Sorghum"). The search was restricted to English-language studies published between January 2015 and March 2025. Both peer-reviewed journal articles and conference proceedings were included to ensure broad coverage. Additionally, backwards snowballing was applied to capture studies not retrieved in the initial database search.

Eligibility Criteria

Studies were included if they

- Focused on AI applications in food systems within Sub-Saharan Africa.
- Specifically referenced applications involving barley, millet, or sorghum.
- Provided empirical data or modeled outcomes related to production, environmental impact, or food security.
- Were published between 2015 and 2025 in English-language peer-reviewed journals or conference proceedings.

Excluded studies were

- Conceptual papers without empirical grounding.
- Reviews, editorials, or opinion pieces.
- Studies not involving AI or not focusing on the Sub-Saharan context.

Study Selection

All retrieved studies were imported into reference management software for deduplication. Title and abstract screening were independently conducted by two reviewers. Full-text articles were retrieved for those that met or potentially met the inclusion criteria. Disagreements were resolved by consensus or by a third reviewer when necessary. The study selection process was documented using a PRISMA 2020 flow diagram (figure 1), detailing records identified, screened, excluded, and included.

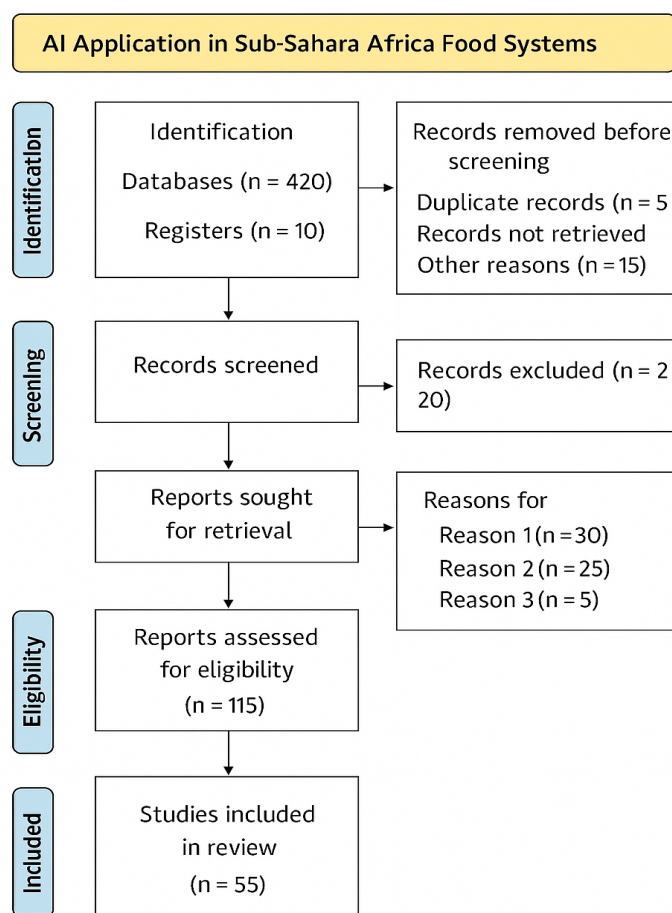


Figure 1. PRISMA 2020 Flow Diagram of the Study Selection Process

Data Extraction and Synthesis

Data were extracted on

- Type of AI technology used (e.g., neural networks, remote sensing, big data analytics).
- Application domain (e.g., yield forecasting, disease detection, resource optimization).
- Cereal crop focus (barley, millet, sorghum).
- Geographic and agroecological context within Sub-Saharan Africa.
- Reported outcomes (e.g., increased yield, reduced emissions, improved resource use).

Studies were synthesized qualitatively to identify key trends, thematic areas, and methodological gaps. Quantitative synthesis was conducted where comparable metrics were reported. Particular attention was paid to the integration of AI with LCA and environmental sustainability metrics. Limitations included inconsistencies in AI models, variability in input data quality, and a lack of region-specific training datasets.

RESULTS

In sub-Saharan Africa, where the average daily calorie intake depends more heavily on consumption of a lower variety of agricultural commodities compared to in other regions, the globalized food system may undermine the stability of food security and nutrition. Thus, understanding and monitoring of the complexity of the geographically and socio-economically diverse food systems of Sub-Sahara Africa are acutely needed.^(13,14,15,16,17) Nonetheless, to unlock the full potential of AI to transform food systems in this region, techno-socio-technical approaches are warranted to ensure local ownership, governance, and sustainability of the technology.

Concerns over the digital divide and data poverty mean access to AI-generated insights could be concentrated among limited powerbrokers. While the potential for a global digital rift loom, intense hopes have risen around the potential of AI for development to advance human progress, equity, and sustainability.⁽¹³⁾ A multitude of transformative initiatives are emerging that offer much to a better understanding of the responsible application of AI for development. Thus, it provides a possible road map to set out some key issues within the domains of policy, innovation, capacity, and infrastructure as a practical guide for individuals and institutions. To promote an inclusive and interdisciplinary research ecosystem, the road map comprises several high-level actions to help focus critique and feedback. These are intertwined with principles for understanding the broader objectives of AI technologies for consideration before engaging with the AI for development initiative. Furthermore, it encourages a proactive role in shaping the strategy to think beyond an individual or reactive standpoint on how these suggestions should be refined, augmented, focused, or reoriented.⁽¹⁴⁾

Historical Context of Food Systems in Sub-Saharan Africa

The food systems of Sub-Saharan Africa have evolved under different historical contexts compared to other regions. Before colonial intervention, some indigenous systems were uniquely suited to their respective natural settings, particularly adapted to the time, labour, resource scarcities and seasons latent in the environment. Colonial rule brought about many changes to the pre-existing food systems, including the introduction of foreign crops and practices, new land tenure systems, and re-zoning of agricultural production.⁽¹⁵⁾

Resultant ‘monoculture’ farming removed the redundancy and ecological buffers that were part of pre-existing farming systems, and which contributed to inherent system resilience to environmental variation. The prioritization of exporting crops, as opposed to subsistence staples, made societies vulnerable to international markets for food security. Post-colonial independence was accompanied by political ‘rebellion’ against the economic structures and divisions of power encoded within the agricultural practices of settlers, many of which were maintained by newly independent states.^(16,17,18,19,20,21) Nonetheless, despite the collapses of some of the more pronounced economic features post-independence, many agrarian systems in the region maintained substantial ‘colonial hangovers’ well into the 1980s.

Central to farming in this region is the recognition of the diversity and interconnectedness of systematized components in agricultural practice. This includes the complex of crops and their geographical division, manure, seed selection, rotational schemes, as well as spatial and temporal flexibilities in the timing of manufacture and storage. This diversity in agriculture is dependent to a great degree upon the generation and maintenance of social networks for ecological support and flexibility. These can take the form of public festivals or the practice of labour sharing. In so doing, societies maintain the redundancy necessary for their farming systems to be flexible and supple to environmental change.⁽²²⁾

Current Challenges in Food Production

Recent reviews analysing the poor performance of agriculture in sub-Saharan Africa (SSA) have placed primary emphasis on the constraints posed by inappropriate fiscal and pricing policies, inadequate extension and marketing systems, and pervasive mismanagement. It is argued that these disincentives and other institutional and infrastructural constraints have combined to create a situation in much of SSA where the increase in aggregate food production has become virtually hopeless.⁽²³⁾ Pertinent evidence in support of this pessimistic view is often seen to lie in the ongoing decline in per capita food production and the growing influx of food aid. While not denying the importance of disincentives and other constraints to African agriculture, this view holds that the most common interpretation of the land surplus argument and the contention highlighted above regarding the adequacy (if not superiority) of the current set of “improved” technologies are both in need of a serious reassessment.^(24,25,26,27)

Substantial proportions of that land are economically unsuitable for agriculture because of desert conditions,

excessive slopes, competition from trees, rock outcroppings, and periodic flooding. Other pieces of land are unsuitable for human and animal populations because of diseases such as bilharzia, trypanosomiasis, and onchocerciasis. Less obvious than these relatively large expanses are the other constraints, but ones that nonetheless exert a significant negative impact on the performance of SSA agriculture, are included. First, there is a high degree of micro variability in land quality, such that the better soils are often either infertile or already under cultivation.^(28,29,30)

Second, soils in much of Africa are inherently unstable, with productivity declining rapidly under continuous cultivation, thereby necessitating a high ratio of fallow to cultivated land. Third, variability in climate, soils, and population densities across SSA requires, at the very least, a differentiated delineation of potentially arable zones. Lastly, land performance is influenced by a wide range of social and economic conditions found in Africa and is adversely affected by exogenous shocks beyond local control.⁽²⁹⁾

Role of Technology in Agriculture

For centuries, nature has determined the outcomes of agricultural activities on the African continent. Despite several interesting improvement attempts that have been made over the years, agricultural activities have still not been completely relieved from blindly depending on favourable environmental conditions. Unfortunately, the average productivity achieved on agricultural activities has still been considerably lower than the targeted value. This demonstrates the vast gap between the current and potential productivity levels of agricultural activities in Africa.⁽²⁸⁾

On the other hand, recent advancements in agricultural automation have brought a fresh breath to agricultural activities in many parts of the world. Since millions of African farmers also work under nearly the same conditions, it is believed that the potential of farming can be significantly improved by implementing related technologies. Agricultural robots stand as the main part of the intelligent farm concept. As a tool for the automation of many agricultural tasks, agricultural robots may bring the potential to overcome many of the current limitations on labour productivity, while also providing the means for precise control over many important parameters that would be otherwise neglected during manual operations.^(2,3,27)

The importance of agriculture cannot be overemphasised as it provides food security, employment and income to the rapidly growing African population. To ensure food security, the continent is expending about 30 billion USD per annum importing food. Climate change affecting the continent is also causing food insecurity. However, to increase yields, farmers use harmful pesticides on crops. Can one predict the use of harmful pesticides on crops before the growing season begins? To determine the predictors of it, the first comprehensive dataset to be used on this issue, which includes weather, field, and soil data, is used. At this point, crops with harmful pesticides mean crops whose allowed pesticides or usage limits of the pesticides exceed the limits given by.^(4,6,26)

AI Technologies in Agriculture

Artificial intelligence (AI) empowered innovations have the potential to transform the current trajectory of African agriculture, from largely subsistence-based to an economically viable and sustainable sector of the domestic and national economy.^(8,21,22,23,24,25,26) New software and hardware designs are increasingly catering towards this idea, with a growing number of entrepreneurs and businesses seeking to solve agriculture-based issues in developing countries. Despite the question of productivity and the long-term sustainability of these systems, the area is seeing robust activity, particularly in Sub-Saharan Africa.

Growth in these systems is boosted by alternative means of digital tech advances in government policy, such as affordable phone and data availability. However, because of health and environmental concerns and constraints, the Africa-based model is still relatively limited. Existing success often befalls simple implementations by NGOs or local stakeholders. Further application of these technologies can be divided into categories. Weed eradication is a major bottleneck in agricultural productivity and can largely be influenced by soil quality. AI-based camera systems aim to detect healthy plants and thus only irrigate these plants.^(23,27)

Such systems are designed not to go into the ground, reducing risk and increasing longevity. Automated tractors can be controlled and programmed by a computer to observe a specific path and save fuel, labour, and time. Example data can be thought of as telemetry for logging soil data, irrigation levels, and climate information for monitoring growth. The necessary output is the nutritional formula of various items to add to the soil to align with the desired future environment. So, this is an example of a big data problem, requiring much information to be collected and a reliable model to predict soil quality. While weather stations are a sufficient source of climate data, a new competitive solution is a miniaturized sensor and setup deployed in numerous areas at a cheaper price.^(3,7,10)

Machine Learning Applications

Machine learning applications are first considered, as they are the most commercialised AI applications

within the food domain. AI research on food systems published within the agricultural domain is then reviewed. This includes research on robotics, the Internet of Things, and other AI technologies that are increasingly applied to the food sector. They are usually aimed at increased food production, but also sometimes at more social aspects.^(3,27)

After determining the appropriate data source and the domain for a specific application, the second challenge is designing proper methods to efficiently exploit the collected data for the prediction. For AI research published within agriculture in the AI domain, the data sources used are mainly satellite images. This form of remote sensing-based data provides huge spatial coverage with high resolution and diversity for the Earth's surface, which frees researchers to either monitor agricultural events or understand the cause.^(12,14,24)

To meet this challenge, classic support vector machine-based methods were typically incorporated with remote sensing data. Such simple features of mean NDVI, max temperature, and precision are used for rough agriculture classification. In the case of the end of harvest being found when 90 % of the pixels have continuously repeated less than a threshold for three years, the mean accuracy was reported as 70 %. With the development of deep learning methods, specific models are leveraged for more classification tasks such as recognition of different crops or the detection of crop residue.^(17,23,24)

Besides, long short-term memory models are involved with spatial models to jointly process spatial and temporal data for more accurate prediction. In the area, the pooled metrics are used to evaluate the average scores of cropping zones created using an algorithm. By doing so, which kind of disease that occurs can be successfully distinguished with an accuracy of around 75 %. Besides the health sector, AI techniques were also introduced to help with food storage and meat.^(5,7,10)

Moreover, Deep Learning-based methods have been found to be particularly effective in complex environments, providing increased success over the application of traditional methods. Various machine and deep learning methods and tools exist for researchers, managers, and stakeholders to apply.^(3,5)

Data Analytics for Crop Management

The goal of this article is to explore the role of AI in the food systems of Sub Sahara Africa to ensure that the coming existence of digitally empowered agriculture is created and governed by smallholders themselves and to address how AI in sub-Saharan Africa can ensure the data analytics revolution can catalyse a power shift in favour of smallholder family farmers. For instance, how can family farmers effectively build, control, and utilise databases as a powerful tool in their agrarian struggles?^(1,2,3)

Given the influx of megainvestments and the aggressive digitalisation agenda of the agribusiness sector in the region, what tools must be developed to enable smallholders to respond with their counter-captures of data and wield them as weapons for empowered engagement? In addition to these practical political questions, what vision(s) can be sketched upon request for a citizen-data landscape that may flourish on the continent, encompassing family farmers but also extending well beyond them?^(3,7,9,13,17,19)

The increasing global deployment of machine learning approaches to satellite imagery for crop management tasks, such as the best practices for data collection and pre-processing, model training, factor importance analysis, and product prototyping, is explored. A project is introduced to address these challenges, resulting in the creation of methodological land maps to support the classification and collaboration.^(3,7,9,13,17,19)

The thematic extent of the methodological land maps is classified into eight different classes to support the classification and sharing of extensions in Sub-Saharan Africa. Major cash crops such as coffee, cotton, sugar cane, tobacco, and various introduced plants are delivered to various countries. Each case study provides a detailed documentation site, high-resolution optical images, land map bands, and a preprocessing description.^(3,7,9,13,17,19)

Robotics and Automation

The impact of artificial intelligence (AI) automation on employment has already begun to be felt, particularly among unskilled workers in sectors that perform routine operations. AI-powered analytics and bots have compelling advantages and efficiency advantages over humans, performing faster, more consistently, and without the need for food and sleep. This has led to an imbalance in the global economy since the benefits of efficiency far exceed the costs of capital investment in technology. Today, AI automation is widely prevalent in industries that can only be conceived of with large amounts of capital, e.g., factories, retail stores, and shipping ports.^(3,7,9,13,17,19)

There are now hundreds of new and innovative applications of AI in development. In contrast, workers in many developing countries, where industrial facilities are small and mechanization technology is not widely accessible, still carry out labour-intensive processes mostly by hand. Given the competitive advantages of AI applied to such processes, automation capabilities could undermine the competitive ability of developing countries and thus retard industrialization and economic growth.

Analysis of more than 200 000 jobs in 29 countries revealed the potential impact from automation. By the early 2020s, approximately 3 % of jobs will be at risk of automation, rising to almost 20 % by the late 2020s, and

by the mid-2030s, 30 % of all jobs will be at risk of automation. For unskilled workers or those without higher education, this figure rises to 44 %. AI has attracted attention for use in the agricultural sector.^(3,7,9,13,17,19)

There are approximately 500 million smallholder farms globally, most of which are managed in developing countries. AI has two primary uses in the agricultural sector: AI-powered agricultural bots that can exceed human capabilities for harvesting crops and picking weeds, and data analysis to predict the weather, optimize planting/harvesting schedules, and calculate fertilizer requirements. The introduction of automation to handling tasks - harvesting and weeding - would see AI competing directly with human labour.^(17,19)

Case Studies of AI Implementation

Although AI-powered innovations have the potential to improve agriculture in SSA, a holistic approach is necessary to monitor and respond to potential negative effects. Awareness of imbalances in the structure of data, such as a monopoly over seeds, data, and pesticides by a single corporation or country, is essential to the development of disruptive solutions, which are transferable with care.

Disruptions connected with agriculture, when properly managed, hold a promise to realign global scales and halt further widening of the agri-food innovation divide between the Global South and North. Complementing the prior strategies with such a holistic 'wide' approach implies the ambition goes far beyond standard guidelines and methodology. However, the alternative would be to take risks with the future, ignoring policies that, when reapplied in fields of AI, have seen how advanced countries enjoyed an estimated revenue uplift, annually accruing from economic power over the marginalised.^(3,7)

In this sense, the stakes are high; by the end of the century, the world economy could be briefly divided into a handful of superpowers with an abundance of all, securing food and textiles, as well as fuel through marine farming, new bio-engineered dietary sources, and responsible AI for environmental control, cross-cut by supercomputing, industrial bio-machines, and biocomputing—and on the other side, a patchy mosaic of small-scale food growers and hi-tech recycling windmills, grounded by soil hackers.^(17,19)

Success Stories in Nigeria

Recently, there have been some insightful success stories concerning the confluence of agriculture, technology, and innovation in Nigeria alone. These give a peek into how much potential lies untapped in agri-food systems across the African continent, where such opportunities are much more abundant.⁽¹⁹⁾

Most noteworthy is the story of Ganji, a drone seed planting startup that helps small-scale farmers plant in less time and with less capital. Ganji was launched in 2019, and two years has already planted on over 800 ha of land, primarily for the Nigerian government, but also farmers across the country. Also relevant is the story of the partners of Farm Innovation, an innovation in Nigeria empowered by blockchain smart contract technology.^(19,21)

Partners in the Farm Innovation model can invest capital in agriculture, allowing and determining how the money will be expended; seed purchase, land preparation, weeding, chemical spraying, harvest, etc., in exchange for profit. Ultimately, profits are distributed among the invested capital. These are just 2 examples, there are many others such as the Badejo farm that is creating a massive, diverse, bio-intensive food forest, commercial production, and a whole ecosystem growth from barren land; farmers can monitor and control their growing conditions with a phone app and their automatic system with seemingly no equivalent across the region, except in South Africa.

Implemented by deep thinking, it is both possible and imperative for Nigeria to become a self-reliant agri-food system, building on innovations across the confluence of technology and agriculture, while learning from other countries. This would allow space for innovation to extend through multiple paradigms of crop preservation, increasing post-harvest life, expanding and rewarding poly-culture farming, and involving the economic network vital to increasing the establishment of large arable land areas.^(17,19,27)

Innovative Practices in Kenya

Emerging immigration trends have resulted in increased population growth, urbanization, and changing consumption patterns as populations shift towards more nutrient-rich and processed foods. In the urban environment, food is disproportionately concentrated and consumed. Urban areas are also where food and nutrition security problems are most concentrated in many places and where most malnutrition problems are growing the fastest. To address these challenges, scientists and practitioners are paying increasing attention to urban food systems. To thrive and be healthy, an individual must have a balanced and nutritious diet.

The more sustainable approach to advancing nutrition security is to ensure access to nutritionally diverse and rich diets, starting at the smallholder farmer level and up the food chain through to consumers. It is through producing a variety of crops and consuming nutrient-dense foods that people can meet their nutritional needs. But how do we efficiently promote and enhance the consumption of these nutrient-rich and diverse foods within the urban environment? A critical problem facing most agricultural-based economies is boosting agricultural production.⁽³⁾

Agriculture in Sub-Saharan Africa is viewed as an essential sector, as most smallholder farmers in developing nations derive their livelihoods through crop production and livestock rearing. Most farmers, mostly in developing countries, produce cereals either at a subsistence level or for the commercial market. Apart from small-scale farming operations, staples such as cereals are often imported into those countries, adding to the population's vulnerability. Despite housing stakeholders in agriculture, prior decisions are claimed to be skewed for consumers and traders in favour of inputs, and policies have neglected smallholder farmers.

The combination of these factors has aggravated food product demand, supply and market distribution within those economies. A significant improvement has been observed in this area due to the introduction of new maize seed varieties as well as new hybrid maize seed varieties. The result is that the number of shaded farms has decreased significantly. To establish the range of food crops being grown by smallholder farmers, data was collected targeting households engaged in agriculture in Makueni and Nyando Sub-Counties.

AI Solutions in South Africa

Africa's population will grow to 1,7 billion by 2030. Demand for food is expected to surpass supply, making African nations vulnerable to chronic hunger. Unlocking agricultural potential, especially in Sub-Saharan Africa (SSA), is imperative for sustainable agri-food innovation systems. SSA accounted for nine of the seventeen innovation achievers, primarily in African agriculture, as part of the knowledge economy. The latest edition of the Agri-food system innovation progress tracker shows SSA accounts for more than half of the innovation performers on the continent. (3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19)

SSA has progressed in areas like research outputs within national boundaries by taking dietary and agricultural biodiversity and land use sustainability into account. AI-based algorithms refer to how large datasets from agricultural management practices, weather predictions, and remotely sensed biophysical conditions can be organized and used to implement agriculture. Already, experiments show that Artificial Intelligence can reduce the costs of agricultural management by a quarter whilst more than doubling the rate at which farmers can respond to changing climatic conditions. (3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19)

Despite SSA's progress with agri-food systems innovation, there remains a substantive investment gap across agri-food systems research, which is necessary to disentangle sustainable innovation triggers and impacts on those systems. AI applications in SSA should be carefully planned to avoid the pitfalls experienced by middle-income nations. AI has already shown the ability to diagnose Learning disorders on a par with or superior to human diagnosticians. It is now applied to estimate the yields of European soya and canola, predict maize production in the US corn-belt, and assess pearl-millet crops in Rajasthan, India.

Top Names of AI in agriculture apps will include: IPPA in Zambia, which is an SMS based service informed by machine learning conjoint, currently in pilot phase, conducted by the USDA and Zimbabwean agricultural researchers. Telecom Namibia to monitor the efficiency and accountability of the fertiliser and farming equipment input scheme surrounding beef processing. Such AI algorithms can identify non-compliance, such as underweight deliveries and off-schedule deliveries. IPPA and Telecom Namibia show that, when planned, AI in agriculture can greatly enhance the efficiency and accountability of agricultural input schemes. Those capabilities can significantly alter power relations and thus provide better bargaining positions for such input scheme recipients. (3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19)

AI and blockchains are considered complementary technologies. Local tech hubs using blockchain software argue that the security and traceability of data storage relate to values that will improve agricultural product certifications and jump-start international export markets. Leveling against fraud and corruption means that fewer opportunities to deviously direct resources will result in equitable distribution of losses. Most instances of known corruption are resolved by decisions to classify prices or outputs artificially, in ways that resemble no significant change in transactions elsewhere. Such secrecy is hard to maintain outside seasonality, as checks and balances bolster transparency. However, pretending non-existent sales or purchases will be quickly detectable by AI scrutiny of sales records, trend movements, and digital landscapes. Itemized prices for any equipment already appear in the public domain, and the hand-written price fixing is a weekend afterthought. Hyper schemes in neighbouring districts are quickly alerted, and corrupt practices swiftly die out. (1,2,3,4,5,6,7,8,9)

Impact Assessment

Modern episodic events spread into the Sahel-Savannah of WCA have led to the setting up of on-station applied sorghum improvement research programs. By 1990, such programs had generated and multiplied over 175 improved germplasm lines that cover most variables of elite breeding material. The Sahelian network partners have released 16 federal early-generation sorghum varieties. Since 1995, more participatory and effective upland rainfed sorghum selection processes have led to the release of 21 varieties. Among these, 14 have been developed by NARS and would have an impact mostly on the upper-middle classes of sorghum producers and are more likely to be commercialized, contributing by up to 25 % within this class.

All research is subject to diminishing returns and must be adapted to the ways of life and sources of capital.

Reasoned agricultural productivity-enhancing research, over time, may engender lessons on the connection between environmental change and farmers' responses, and, through an efficient technology delivery system, in partnership with the private sector, generate broadly based welfare improvement and poverty alleviation. Socio-economical liberalization of the markets and devaluation of the FCFA in 1991, have affected grain-legume composite budget allocations of institutional partners. Any cross regional Sahelian sorghum research network would have to be based first and foremost on an efficient exchange and evaluation, including quarantine measures for major biotic stresses, of the most drought-adapted germplasm available. It would need to adopt some standardized, albeit limited number, professionally managed, multi-locational trials schemes.

Social Implications

In contrast to its economic benefits, automation poses consequences - intended and otherwise - larger and deeper than the sum of its technical parts. While industrial-scale AI applications permit unparalleled possibilities for data handling and decision-making, it also presents opportunities for decision-making and discretion in employment conditions that are typically situated in the last defensive bulwark of human employment.

Broadly described as social ramifications, these consequences carry potential impacts across a web of relationships as work changes; family networks diversify and converge ever more numerous streams of precarious income (and risks) into shared pools; new power distributions within households; and community ties of long provenance unravel and reweave in refigured geographies. As automation takes hold, the sting of obsolescence is aggravated.

Increased questions are being voiced about the motivation of external actors bringing AI to African agriculture. The initiatives are portrayed as a combination of innocently well-intended misguidedness and an age-old danger to self-determination and, here especially, sovereignty. Critics see the structural reality of many AI applications in the global agricultural South as domination, profit-seeking, resource-hoarding, and futures manipulation. Perceived as a poisoned chalice, such initiatives could become the proverbial Trojan horse - outwardly benign but cosmically catastrophic once within. This is a particularly dangerous time for AI investments in African agriculture, as groundswells of resistance and restoration are growing, and the imperialist aspirations of newly formed colonial counts are turning grain into gold.

Barriers to AI Adoption

Artificial intelligence (AI) has the potential to help solve many of Africa's pressing problems, particularly food security, if adopted in time. However, there are risks that AI will increasingly marginalize the poor and disadvantaged, who will not have the means to leverage technological advancements. In agriculture, applying AI could contribute to a more just environmental and agricultural system, as concerns over 'planetary boundaries' increase, including population growth, over-consumption and the risks of 'business as usual' responses. Current trajectories will keep Africa disproportionately behind by 2050. AI can be harnessed to reduce food scarcity and increase the potential for more equal development and interests, therefore, it is important to address these challenges and clear the potential advantages of adopting AI early in the Global South, given the current inequities in the world system.^(23,24,25)

The role of AI may also be more practically referred to in the recent general assembly declaration by the United Nations. The role of AI aims to support the agriculture mapping and management within climate change domain. Before addressing the local application study, particularly for South Africa, it might be relevant to focus on the status of the background and relevance of AI and agriculture with a focus on sub-Saharan Africa south of the Sahara. This region has continued to be challenged by various issues of food insecurity. As population growth will result in greater food demand by 2050, climate change will also cause a decrease in food production in several countries on the continent.⁽²⁵⁾

This unsafe situation draws attention to increasing the adaptation capacity and the role of AI in agriculture mapping. Africa is exceptionally vulnerable to food insecurity resulting from global environmental change, climate change, population growth and negative trade balances that continue to threaten the livelihood of political sustainability, ecosystem and human well-being. Furthermore, the prevailing agricultural systems--often with outdated techniques, little financial input, and unpredictable climatic conditions--endure crop failures due to pests and diseases, frequently invasive. A number of these problems are difficult to diagnose manually and at an early stage, risking the fast spread of illness, thus leading to high losses. Instances of dangerous crops include, for example, maize crops in sub-Saharan Africa. Africa's ability to raise this problem is hindered by several critical restrictions.^(1,2,5)

The data necessary to make informed and appropriate decisions is unavailable, partially due to ongoing unstable and improper harvest data. Labour shortages and a lack of agricultural proficiency and skills also obstruct the diagnosis and care of the disease. However, AI offers new opportunities to work towards redressing a host of agricultural problems through advanced diagnosis and treatment of illnesses, and within the next years, there is quickly evolving AI technology that could significantly affect the environment. At this critical

juncture, explicit and proactive AI policies are necessary that address potential harm, uncertain benefits and work in the interest of Africa's poor and marginalized.

Infrastructure Challenges

The agricultural sectors in Sub-Saharan Africa's food system are characterised by basic farming technologies, primary production technologies, limited rural infrastructure, and a predominantly rain-fed farming system. There are several infrastructure challenges for 15 African countries in Sub-Saharan Africa, including water supply, irrigation facilities, transportation access, and communication. Water infrastructure is a critical input for agriculture, benefiting land provision. The infrastructure coverage rate in the sample African countries in 2018 is shown in the brackets, such as water supply (40 %), sewage (36 %), road access (60 %), and mobile access (52 %).^(2,3,4,5,6,7,8,9,10,11,12,13,14,15,16)

The coverage rate of irrigation in arable land in the sample countries is up to 51 %. It also reports that the road and mobile access in Sub-Saharan Africa (SSA) has greatly improved in the past 10 years. However, the coverage rate of water and sewage infrastructures is relatively lower than that in other middle-income countries (MICS). There is substantial room for improvement regarding the coverage rate of sewage infrastructures. Separately, some key infrastructures vary largely in these countries, such as irrigation and mobile in Rwanda and Zimbabwe. The infrastructure coverage rate has also varied widely among different regions in these African countries. In 2018, roads and mobile network infrastructure had a higher coverage rate in Africa. However, water supply and sewage facilities are relatively underdeveloped, especially in the Central African region.^(2,3,4,5,6,7,8,9,10,11,12,13,14,15,16)

Financial Constraints

Exists a need for transformative innovation along the entire African food system, such innovation includes the entire food value chain: rural inputs and services, natural resource management and land use planning, rural labour, transportation, storage, processing, marketing, rural household, nutrition knowledge and practice, and consumption habits. With only a few exceptions, technology and innovation policy in sub-Saharan Africa has focused mainly on something novel created in hi-tech cities by researchers and engineers with tertiary education. The agricultural policy has long been dominated by a focus on mechanical innovations linked with modern seeds, fertilizer, and pesticide use. Operation and results were defined in terms of standalone agricultural production increase, with little consideration of the diverse and complex types of innovation and the multi-spectral aspects of agriculture concerning socio-economic and political contexts.^(2,3,4,5,6,7,8,9,10,11,12,13,14,15,16)

There are knowledge gaps related to the impacts of the application of Artificial Intelligence and Machine Learning in Africa and other developing regions of the world, This review aims to fill this gap via a collation and analysis of worldwide literature on this subject. Scientific production on the economic implications of AI/ML for global food security and the future of agriculture, including climate change adaptation, is booming globally, especially in OECD countries. Conversely, there is a severe lack of scientific production and engagement with the implications of AI/ML for agriculture, social policy, and food security in Africa and developing regions of the Global South.^(2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,30) Such trends are important as Africa seems to be the next fertile ground for the application of AI and ML, and its economic implications for agricultural and poverty changes. The thought base of the review is based on the relevance to low- and middle-income countries. The developmental dimension has also been included in Africa and other developing regions of the world. I, therefore, anticipate that this review shall serve as an innovative concept and real-world case study concerning the implications of AI and ML for global food and poverty issues.

Knowledge Gaps

AI technologies offer a much-needed transformative disruptive potential that could significantly foster the non-linear growth of Sub-Saharan Africa food systems to provide affordable, reliable, substantial and sustainable food to all in a more inclusive, efficient and equitable way, potentially leading to their reinforcement, resilience and sustainability. There is an emerging demand for a transformative, sustainable policy-driven research program to better understand, design and implement AI technologies in the food sector, with a focus on the most vulnerable countries and communities.^(9,10,11,12,13,14,15,16)

In this first-of-its-kind synthesis, machine learning and deep learning techniques in agriculture are critically evaluated in the African context. A knowledge synthesis starts by identifying short- and medium-term challenges faced by small-scale farmers in Sub-Saharan Africa, followed by potential key AI techniques that can address those challenges. It concludes with the identification of knowledge gaps that can be closed with further research.^(9,10,11,12,13,14,15,16) There is written and theoretical support that a framing of AI technologies that would emphasise data quality, context variety and traceability could uniquely promote agro-ecological practices and sustainable food consumption, thus generating potential health benefits that might greatly help the alleviation of Sub-Saharan Africa public health troubles, landscape regeneration, rural sustainable development and poverty eradication.

CONCLUSIONS

The integration of Artificial Intelligence (AI) into Sub-Saharan Africa's (SSA) food systems presents a transformative opportunity to address long-standing agricultural challenges and enhance food security. Despite the region's historical and infrastructural constraints, AI offers the potential to optimize crop yields, improve resource efficiency, and support climate-resilient farming. Through innovations such as remote sensing, machine learning, and predictive analytics, farmers can make more informed decisions, reduce post-harvest losses, and manage pests and diseases more effectively. However, the path forward requires inclusive and locally grounded strategies to avoid deepening existing inequalities.

Ensuring equitable access to data, infrastructure, and training is vital for smallholder farmers to benefit from AI advancements. Furthermore, robust governance frameworks must be established to manage data sovereignty and mitigate risks of monopolization and socio-economic disruption. As this review demonstrates, responsible deployment of AI, paired with policy reform, capacity building, and stakeholder collaboration, can catalyze sustainable development across SSA's agri-food systems and empower communities to overcome future challenges with resilience and autonomy.

BIBLIOGRAPHIC REFERENCES

1. Mekonnen SA, Jalata DD, Onyeaka H. Building resilience in Sub-Saharan Africa's food systems. *Food Energy Secur.* 2024. <https://doi.org/10.1002/fes3.563>
2. Nchanji EB, Ageyo OC, Puskur R, Templer N, Maereka EK. Towards gender-transformative metrics in seed system performance measurement: insights for policy and practice in Sub-Saharan Africa. *CABI Agric Biosci.* 2024;5(1):83. <https://doi.org/10.1186/s43170-024-00291-6>
3. Mperejekumana P, Shen L, Gaballah MS, Zhong S. Exploring the potential and challenges of energy transition and household cooking sustainability in sub-Saharan Africa. *Renew Sustain Energy Rev.* 2024;199:114534. <https://doi.org/10.1016/j.rser.2024.114534>
4. Wudil AH, Usman M, Rosak-Szyrocka J, Pilař L, Boye M. Reversing years for global food security: A review of the food security situation in Sub-Saharan Africa (SSA). *Int J Environ Res Public Health**. 2022;19(22):14836. <https://doi.org/10.3390/ijerph192214836>
5. Kayusi F, Chavula P. Enhancing Urban Green Spaces: AI-Driven Insights for Biodiversity Conservation and Ecosystem Services. *LatIA.* 2025;3:87. <https://doi.org/10.62486/latia202587>
6. Kayusi F, Chavula P. Enhancing Wetland Restoration through Machine Learning-Based Decision Support Systems. *LatIA.* 2025;3:81. <https://doi.org/10.62486/latia202581>
7. Stein H. Policy and performance in African agriculture since independence: critical reflections. In: *Handbook of African Economic Development.* 2024. <https://doi.org/10.4337/9781800885806.00022>
8. Mechiche-Alami A, Yagoubi J, Nicholas KA. Agricultural land acquisitions unlikely to address the food security needs of African countries. *World Dev.* 2021. <https://doi.org/10.1016/j.worlddev.2020.105384>
9. Sadiq FK, Ya'u SL, Aliyu J, Maniyunda LM. Evaluation of land suitability for soybean production using GIS-based multi-criteria approach in Kudan Local Government area of Kaduna State Nigeria. *Environ Sustain Indic.* 2023;20:100297. <https://doi.org/10.1016/j.indic.2023.100297>
10. Abdulai AR. (GR) or neoliberal entrenchment in agri-food systems? Exploring narratives around digital agriculture (DA), food systems, and development in sub-Saharan Africa. *J Dev Stud.* 2022. <https://doi.org/10.1080/00220388.2022.2032673>
11. Choruma DJ, Dirwai TL, Mutenje M, Mustafa M, Chimonyo VGP, Jacobs-Mata I, et al. Digitalisation in agriculture: A scoping review of technologies in practice, challenges, and opportunities for smallholder farmers in sub-Saharan Africa. *J Agric Food Res.* 2024;101286. <https://doi.org/10.1016/j.jafr.2024.101286>
12. Johnson ME, Farris J, Morgan S, Bloem JR, Ajewole K, Beckman J. Africa's Agricultural Trade: Recent Trends Leading up to the African Continental Free Trade Area. 2022.
13. Ozor N, Nwakaire J, Nyambane A, Muhatiah W, Nwobodo C. Enhancing Africa's agriculture and food

systems through responsible and gender inclusive AI innovation: insights from AI4AFS network. *Front Artif Intell.* 2025;7:1472236. <https://doi.org/10.3389/frai.2024.1472236>

14. Ahmad A, Liew AX, Venturini F, Kalogeras A, Candiani A, Di Benedetto G, et al. AI can empower agriculture for global food security: challenges and prospects in developing nations. *Front Artif Intell.* 2024;7:1328530. <https://doi.org/10.3389/frai.2024.1328530>

15. Chhetri KB. Applications of artificial intelligence and machine learning in food quality control and safety assessment. *Food Eng Rev.* 2024. <https://doi.org/10.1007/s12393-023-09363-1>

16. Bidyalakshmi T, Jyoti B, Mansuri SM, Srivastava A, Mohapatra D, Kalnar YB, et al. Application of Artificial Intelligence in Food Processing: Current Status and Future Prospects. *Food Eng Rev.* 2024;1-28. <https://doi.org/10.1007/s12393-024-09386-2>

17. Victor B, Nibali A, He Z. A systematic review of the use of Deep Learning in Satellite Imagery for Agriculture. *IEEE J Sel Top Appl Earth Obs Remote Sens.* 2024. <https://doi.org/10.1109/JSTARS.2024.3501216>

18. Cravero A, Pardo S, Galeas P, López Fenner J, Caniupán M. Data type and data sources for agricultural big data and machine learning. *Sustainability.* 2022;14(23):16131. <https://doi.org/10.3390/su142316131>

19. Chavula P, Kayusi F, Agura Kayus B. Linking New Information Technologies to Agricultural Economics: The Role of Artificial Intelligence Integration. *LatIA.* 2025;3:326. <https://doi.org/10.62486/latia2025326>

20. Elbasi E, Mostafa N, AlArnaout Z, Zreikat AI, Cina E, Varghese G, et al. Artificial intelligence technology in the agricultural sector: A systematic literature review. *IEEE Access.* 2022;11:171-202. <https://doi.org/10.1109/ACCESS.2022.3232485>

21. Wang M, Li X. Application of artificial intelligence techniques in meat processing: A review. *J Food Process Eng.* 2024. <https://doi.org/10.1111/jfpe.14590>

22. Sarker T, Deen RA, Ghosh D, Mia N, Rahman MM, Hashem MA. AI driven approach and NIRS: A review on meat quality and safety. *Meat Res.* 2024;4(6). <https://doi.org/10.55002/mr.4.6.105>

23. Qiao J, Zhang M, Wang D, Mujumdar AS, Chu C. AI-based R&D for frozen and thawed meat: Research progress and future prospects. *Compr Rev Food Sci Food Saf.* 2024;23(5):e70016. <https://doi.org/10.1111/1541-4337.70016>

24. Tzachor A, Devare M, King B, Avin S, Ó hÉigeartaigh S. Responsible artificial intelligence in agriculture requires systemic understanding of risks and externalities. *Nat Mach Intell.* 2022;4(2):104-109. <https://doi.org/10.1038/s42256-022-00440-4>

25. Abrar-Ul-Haq M, Sankar JP, Akram F, Malik HAM. Harvesting prosperity: AI-powered solutions for household poverty reduction through smart agriculture. In: 2024 IEEE 1st Karachi Section Humanitarian Technology Conference (KHI-HTC). 2024:1-5. <https://doi.org/10.1109/KHI-HTC60760.2024.10482025>

26. Mhlanga D. Artificial intelligence in the industry 4.0, and its impact on poverty, innovation, infrastructure development, and the sustainable development goals: Lessons from emerging economies. *Sustainability.* 2021;13(11):15788. <https://doi.org/10.3390/su13115788>

27. Chavula P, Kayusi F, Agura Kayus B. Application of Artificial Intelligence in Tree Care in Sub-Saharan Africa. *LatIA.* 2025;3:325. <https://doi.org/10.62486/latia2025325>

28. Korinek A, Stiglitz JE. Artificial intelligence, globalization, and strategies for economic development. NBER Working Paper No. 28453. 2021.

29. Mannuru NR, Shahriar S, Teel ZA, Wang T, Lund BD, Tijani S, et al. Artificial intelligence in developing countries: The impact of generative artificial intelligence (AI) technologies for development. *Inf Dev.* 2023. <https://doi.org/10.1177/02666669231200628>

30. Javaid M, Haleem A, Khan IH, Suman R. Understanding the potential applications of Artificial Intelligence in the Agriculture Sector. *Adv Agrochem*. 2023. <https://doi.org/10.1016/j.aac.2022.10.001>

FINANCING

The authors did not receive financing for the development of this research.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

AUTHORSHIP CONTRIBUTION

Conceptualization: Fredrick Kayusi.

Data curation: Fredrick Kayusi, Petros Chavula.

Formal analysis: Fredrick Kayusi, Petros Chavula.

Research: Fredrick Kayusi, Petros Chavula.

Methodology: Fredrick Kayusi.

Software: Fredrick Kayusi, Petros Chavula.

Validation: Fredrick Kayusi, Petros Chavula.

Display: Fredrick Kayusi, Petros Chavula.

Drafting - original draft: Fredrick Kayusi.

Writing - proofreading and editing: Fredrick Kayusi, Petros Chavula.