LatIA. 2024; 2:88
doi: 10.62486/latia202588
ISSN: 3046-403X

REVIEW

Leveraging Artificial Intelligence for Enhancing Wheat Yield Resilience Amidst Climate Change in Sub-Saharan Africa

Aprovechamiento de la Inteligencia Artificial para Mejorar la Resiliencia del Rendimiento del Trigo ante el Cambio Climático en África Subsahariana

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Cite as: Chavula P, Kayusi F, Juma L. Leveraging Artificial Intelligence for Enhancing Wheat Yield Resilience Amidst Climate Change in Sub-Saharan Africa. LatIA. 2024; 2:88. https://doi.org/10.62486/latia202588

Submitted: 27-02-2024 **Revised:** 21-06-2024 **Accepted:** 15-09-2024 **Published:** 16-09-2024

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ABSTRACT

The introduction of a deep learning-based method for non-destructive leaf area index (LAI) assessment has enhanced rapid estimation for wheat and similar crops, aiding crop growth monitoring, water, and nutrient management. Convolutional Neural Network (CNN)-based algorithms enable accurate, non-destructive quantification of seedling leaf areas and assess LAI across diverse genotypes and environments, demonstrating adaptability. Transfer learning, known for efficiency in plant phenotyping, was tested as a resource-saving approach for training the wheat LAI model. These advancements support wheat breeding, facilitate genotype selection for varied environments, accelerate genetic gains, and enhance genomic selection for LAI. By capturing diverse environments, this method can improve wheat resilience to climate change. Additionally, advances in machine learning and data science enable better prediction and distribution mapping of global wheat rust pathogens, a major agricultural challenge. Accurate risk identification allows for timely and effective control measures. Moreover, wheat lodging prediction models using CNNs can assess lodging-prone varieties, influencing selection decisions to improve yield stability. These artificial intelligence-driven techniques contribute to sustainable crop growth and yield enhancement, especially in the context of climate change and increasing global food demand.

Keywords: Deep Learning; Leaf Area Index; Convolutional Neural Networks; Wheat Breeding; Climate Resilience; Plant Phenotyping.

RESUMEN

La introducción de un método basado en aprendizaje profundo para la evaluación no destructiva del índice de área foliar (IAF) ha mejorado la estimación rápida en trigo y cultivos similares, facilitando el monitoreo del crecimiento, el manejo del agua y los nutrientes. Los algoritmos basados en redes neuronales convolucionales (CNN) permiten la cuantificación precisa y no destructiva del área foliar de plántulas y la evaluación del IAF en diversos genotipos y entornos, demostrando su adaptabilidad. El aprendizaje por transferencia, conocido por su eficiencia en la fenotipificación de plantas, fue probado como un enfoque que ahorra recursos en el entrenamiento del modelo de IAF para trigo. Estos avances apoyan la mejora genética del trigo, facilitan la selección de genotipos para distintos ambientes, aceleran las ganancias genéticas y optimizan la selección genómica para el IAF. Al capturar una mayor diversidad ambiental, este método puede mejorar la resiliencia del trigo al cambio climático. Además, los avances en aprendizaje automático y ciencia de datos permiten una mejor predicción y mapeo de la distribución de los patógenos del óxido del trigo, un desafío agrícola global. La identificación precisa del riesgo posibilita medidas de control oportunas y eficaces. Asimismo, los modelos de predicción del encamado del trigo mediante CNN pueden evaluar variedades propensas al encamado, influyendo en su selección para mejorar la estabilidad del rendimiento. Estas técnicas basadas en inteligencia artificial contribuyen al crecimiento sostenible de los cultivos y al aumento del rendimiento, especialmente frente al cambio climático y la creciente demanda mundial de alimentos.

Palabras clave: Aprendizaje Profundo; Índice de Área Foliar; Redes Neuronales Convolucionales; Mejoramiento del Trigo; Resiliencia Climática; Fenotipificación de Plantas.

INTRODUCTION

One of the prime concerns due to emerging and acute climate change in developing countries, particularly in sub-Saharan Africa, is reliable food production that can sustain livelihoods for increasing populations. The extent of demographic growth, which is highest in sub-Saharan Africa compared to other regions of the world, doubles the pressure to achieve commercial agricultural productivity, which is beyond existing gains. One major smallholder cereal crop is wheat, which is primarily grown in the temperate highland ecosystem, and in most regions of this ecosystem, there is a strong upward trend in temperature, associated with changing rainfall patterns, therefore exerting an elevated abiotic pressure. Given the importance of wheat and potential concerns about future climate, a priority is to develop novel resilience mechanisms that can maintain wheat yield. Such a resilience mechanism can be achieved through modern scientific techniques, including the application of artificial intelligence.(1,2,3,4)

With huge storage capacities and architectures, artificial intelligence can be applied to extensive datasets to depict complex responses generated from wheat. These complex responses contain gene regulation, phenotypic to micro-environmental associations, and diverse and dynamic interactions among weather, nutrient variables, and cropping processes. By influencing such a diverse range of genomic to micro-level interactions, artificial intelligence can provide and develop data-driven problem-aware solutions, which were hitherto impossible to solve and design based only on classic statistical models. Specifically, this could include gene expression, which can be realized with the support of gate classification algorithms that are incorporated with medical techniques, where classification is improved in the presence of missing or distorted data.

Through phenotype levels influenced by heavily covariate interactions, which could involve convolutional neural networks and crop yield realizations influenced by diverse and complex interactions, including agents such as seasonal climate responses, which recurrent neural networks can identify. The advances in numerous research disciplines, together with sensor technology and the influence of artificial intelligence, are revolutionary agricultural progress that, established in many developed countries, is breathing fresh air into developing countries. Given the perennial scarcity of resources, the evolutionary integration and benefit of this science should be understood in advance, and scientists from sub-Saharan Africa must be able to include themselves in the advancement of its foundations. This is particularly relevant and critical to vulnerable regions where adaptive agricultural innovation is paramount to maintaining economic strength.(5,6,7,8)

Sub-Saharan Africa (SSA) produces 25 % of the global wheat yield. However, the demand for wheat is continuously rising in SSA due to a population increasing at a rate of 3 % per year, among other non-income-related causes. Despite such a promising landscape, wheat productivity in SSA is among the lowest globally due to biotic, abiotic, socio-economic, and political factors. Despite significant efforts by national agricultural research systems and other partners that boost wheat production in countries like Ethiopia, much help is still needed, especially amidst the emerging challenges like climate change. Climate change, compounded with land degradation, the presence of diseases and parasites, and variability and/or reduced nature of rainfall, complicates efforts to optimize genetic outputs.(9,10,11,12,14)

In this era of technological advancements, recently emerging technologies like remote sensing and artificial intelligence enable continuous and individualized plant evaluation under real field conditions. Frequently, crop variance exceeds experimental variance, and this, in the long run, may turn into a lack of interest in proven wheat varieties by smallholder farmers or irregular crop introduction activities by seed regulatory agencies. Furthermore, the optimal application of fungicides, herbicides, insecticides, and other crop response variables is commonly searched to sustain healthy wheat plants. In the current climate change setting, the availability of large data sets in crop sciences is linked with many other big data-related challenges. Furthermore, for machine and deep learning schemes to work automatically, a great amount of data that has a high impact on the algorithm to learn is a must.(15,16,17,18)

https://doi.org/10.62486/latia202588 ISSN: 3046-403X

DEVELOPMENT

Research Objectives

This study has three interrelated diagnostic, predictive, and prescriptive research aims. The overarching goals are to diagnose the performance of wheat-climate links, determine which predictive model's performance is best, and prescribe the tasks that can operationalize and optimize multiple dimensions of sustainable food systems in Sub-Saharan Africa. The specific aims include examining the stationarity of weather series, locating probable predictors, comparing performance criteria of predictive models, and characterizing AI algorithms as decision support tools in precision agriculture in the context of small-scale farming systems. More awareness, sensitivity, and responses are needed around climate change impacts on crop systems in biotechnology and artificial intelligence applications for more inclusive sustainable food systems.

The first diagnostic objective seeks to investigate the interactions of climate trends over calendar time in the context of wheat productivity in Ghana. This will be achieved by observing the shape of the relationship and the presence of marked changes, and whether the change points have been temporally consistent over different seasons. The second diagnostic objective aims to locate the secondary weather station closest to the farm location using cumulative distribution functions of precipitation and temperature. An exploratory geospatial data analysis is used to highlight secondary weather stations that have similar precipitation or temperature distribution around the farm location. On the other hand, discrepancies between the distance to the closest secondary weather station location will be exploited using summary statistics.

Artificial Intelligence in Agriculture

Using artificial intelligence (AI) to tackle grand challenges in agriculture is becoming invaluable. The interactive system of AI, including the subsets of machine learning, deep learning, and predictive modeling, contributes to enabling faster tracking of data processing, development of robust decision-support systems, disease identification, and availability of prediction systems globally. Recently, AI-driven solutions have recorded some successes in enhancing agricultural sustainability in the developing world. The rise in breakthroughs such as improved plant and animal breeding, natural language processing for enabling conversation-based farmer advice in real-time, facial recognition tools for improved animal group feeding, smart robots that aid crop weeding, predictive and detection algorithms for early animal diseases, and hyper-location lesion detection in real-time has initiated increased interest in and demand for the opportunities it pledges.[19,20,21]

Contrariwise, the application of AI for crop yield and resilience enhancement in sub-Saharan Africa is not robust, especially amidst the rising food security concerns it faces. The ability to bridge this gap by leveraging the vast data hidden in Africa's wheat archives offers potential for reducing its yield gap. Unlocking data trends using improved data collection and pre-processing procedures is important to generate efficient AI-driven models, breeding hope for generating long-term impact in agricultural sustainability.

Overview of AI in Agriculture

Advances in artificial intelligence (AI) are accelerating improvements in many scientific areas, including agriculture. AI technologies, such as drones, satellite imagery, robotics, and blockchain, along with software development, require access to well-annotated, high-quality data, as well as the expertise of data scientists. The creation of an AI application in agriculture is highly complex, from developing computer vision, natural language processing, and machine learning algorithms to the deployment of the technology. The text outlines how specific AI tools, through collaboration across disciplines, can contribute to addressing some of the most critical issues in wheat production, while discussing the opportunities that AI applications in agriculture present for smallholder farming in Sub-Saharan Africa. Technologies of the fourth industrial revolution, such as robotics, and applications of artificial intelligence (AI) are being developed and deployed in diverse horticultural and grain crops, where operations are standardized and accessibility to precision agriculture data and information is relatively widespread. Yet, AI expertise and access to high-quality precision data remain limited for wheat, an under-researched staple grown in larger areas under a rich geographic diversity, in different socio-economic conditions, and tends to have yield variability due to climatic extremes.[22,23,24,25,26,27]

AI Applications in Wheat Farming

AI has played and will continue to play an important role in driving agriculture's transformation. Its applications in improving wheat production hinge on the following categories: (1) agronomic techniques for crop breeding, such as site-specific crop management and precision approaches such as variable rate seeding based on realistic simulation of plant density and arrangement, recurrent selection through interplant mixing, and automated plant imaging and phenotype analysis; (2) non-DNA molecular techniques such as vibrational spectroscopy analysis that is coupled with supervised learning algorithms to enable rapid, non-destructive, and accurate quantitative and qualitative analysis of active ingredients in wheat varieties; bio-based sensors to support precision approaches to measure crop water status under reduced irrigation; (3) integrated disease

https://doi.org/10.62486/latia202588 ISSN: 3046-403X

management through hyper-spectral, hyperspectral, or thermal imaging techniques that can be used to identify diseases, coupled with unsupervised learning methods; (4) predicting wheat yields by advanced machine learning models; (5) facilitating and improving critical climatic windows, such as predicting rainfall onset to capture key agronomic activities like wheat planting.[2,8,28,29]

Challenges of AI Adoption in Sub-Saharan Africa (SSA)

The benefits of the AI approach concerning the enormous and granular genomic and field data in potential enhanced wheat yield resilience amidst climate change are evident. Unfortunately, there are existing and potential constraints hampering the full adoption of the AI approach in Africa generally and sub-Saharan Africa in particular. We present those challenges with the following objective in mind: to shine a spotlight on those challenges and provide an initial blueprint to the field in comprehensively addressing them in the future. The primary objective of this text is transparency; as such, we do not aim to achieve an exhaustive collection of challenges but rather map the significant milestones that need to be addressed in the future. Indeed, addressing the challenges in the ecosystem of AI adoption involves learning by doing; thus, other challenges shall manifest as we embark on the journey of deploying AI for crop genetic improvement.[30,31,32,33,34,35]

The data storage infrastructural capacity of sub-Saharan Africa does not measure up to the demands of processing big data driven by data acquisition sensors and platforms. First and foremost, it is crucial to have access to digital infrastructure capable of storing vast data coming from both the human and the computational domain as a result of genomics and field data for wheat yield resilience prediction models to succeed. The digital infrastructure requires a farm information communication technology-enabled database and data repository capable of acquiring, storing, and processing wheat field phenotypic, climatic, soil, crop management practices, and genetic/genomic sequencing data. Next, the database repository management infrastructure should have both hardware and software for data governance, curation, scalable storage, data quality maintenance and assurance, and accessibility and interoperability support for decision-making. Such data farms foster and nurture a decision-centric crop research culture capable of provisioning domain data management services that fit the needs of agricultural experiment designs. Moreover, participatory traits and staged data sharing strategies can be built on crops of importance at seed stage companies, industry, and research institutions based on a transparent understanding of their influences on information access and benefit sharing. The lack of suitable crop improvement data management may inhibit a holistic view of how enhanced wheat yield resilience models can be possible in sub-Saharan Africa. With privacy and compliance issues important to stakeholders and data subjects, a collaboration model should also be established to govern who manages data access, safe handling techniques to prevent data privacy leaks, and support for future semantic search for wheat research purposes.[36]

Infrastructure and Connectivity Challenges

About sub-Saharan Africa, access to technology services is limited and very variable across regions within countries. Infrastructure plays a critical role in enabling such technology services. Infrastructure is essential: without it, companies cannot deploy technology, and technology solutions have limited impact. Africa has seen substantial progress in the development of its infrastructure over the last decades, with improved roads and ports, more extensive and robust telecommunications networks, and expanded access to electricity. However, there remain large gaps in the infrastructure of many African countries and regions. Constraints in the quality and capacity of power, water, and transport infrastructure, as well as technology infrastructure like telecommunications, can seriously impede the growth of tech innovation markets and tech-enabled services.[37,38,39]

Sub-Saharan Africa faces significant infrastructure development challenges. Its infrastructure is seriously underdeveloped, so that, for example, the phone system in the region is worse than that in India in every aspect except density, where India had 14 lines per 100 people in 1999 and sub-Saharan Africa had 1,3. A breathtaking range of service inadequacies hampers growth in the many countries of sub-Saharan Africa. Out of a population totaling 625 million people, there are less than 1 million telephones, while fixed-line penetration per capita is only 0,13 telephones per 100 persons. Restricted railway capacity and reliance on poorly maintained roads make moving goods an expensive and unreliable proposition, while between 60 % and 90 % of all freight moves by truck and bus. Such problems are a constant source of friction for all firms, for multinational corporations as much as for small domestic manufacturers. Only 33 % of the entire population in the 48 countries in the region have access to reliable power. Only 8 % of the 625 million inhabitants have access to electricity, with the situation little better in towns than in rural areas.[40]

In addition to these constraints, the price of such services, where they exist, is high. Users normally face long delays and high costs in obtaining basic telecommunications services. Average non-residential fixed charges in sub-Saharan Africa per equivalent main line at 1999 PPP rates amounted to a significant amount per year, more than 25 times the average rate in Europe, even after adjusting for the purchase price of a new main line. Similarly, delivery times average 215 days, while in Europe delivery takes 30 days. Moreover, approximately

85 % of telephone exchanges in the region cannot accommodate new digital or optical fiber connections. Transport costs paid by manufacturing firms in sub-Saharan Africa for input delivery and for input and/or output movement are among the highest in the world. A comparison of transport and communication costs indicates that these cost disadvantages are a significant barrier to Africa's integration into world markets. Costs remain opaque, hampering customer choice and forcing up telecom prices.[41,42,43,44]

Barriers to the deployment of modern telecommunications in Africa are less pronounced than they were in most other areas of the world before the mid-1990s because many African countries had largely ignored or severely restricted access to telecommunications. Since then, Africa has seen, in comparison to other regions, substantial new fixed and mobile operator licenses, and investment activity has been brisk. Between 1995 and 1999, Africa added a notable percentage of the world's fixed lines, mobile subscribers, and Internet host computers. All of sub-Saharan Africa and part of North Africa are linked to global satellite systems. High-frequency radio relays provide nearly all intercity interexchange connections. Submarine branches of the Intelsat system and a geostationary Intelsat satellite provide capacity to all major separate terrestrial networks. Due to a lack of competition, inadequate regulatory frameworks, and low demand due to high prices, however, access to telecommunications still lags regarding market demand in Africa, including sub-Saharan Africa; and this lags behind every other region of the world.[45,46]

Data Availability and Quality

The importance of big data in AI cannot be overemphasized. The advancement in AI research nowadays that we hear continually in mainstream media outlets is largely attributed to the fact that sizable and high-quality data is being used to train these AI algorithms. Indeed, to scale AI nationally from farm level, reliable data are pivotal. However, data for training wheat AI technologies, especially at the county and ward levels, are limited in the sub-Saharan African region. Additionally, most of the existing global datasets are associated with latencies, definitions, units, spatial quality, and availability challenges due to their mixed origin, quality, and spatial extent. Barriers to scaling demand creation reside in the enormous data constraints stalling the efforts and momentum to develop endemic digitalization, equipment, and human capacity to map wheat activities or other crops in most sub-Saharan African countries.[47,48,49,50,51,52,53]

Despite the emerging framework solutions from new crop area mapping projects, barriers to building common databases with mandatory data-sharing requirements need to be addressed, especially among government research institutions. This is more so in the case that climate change constitutes a combination of both episodic and chronic events, most of which might last towards the end of the century, by which time a significant proportion of the African population will likely be dependent in one way or another on agricultural products. Without an available data-driven environment, machine learning solutions, like other technologies, will be extremely difficult to develop and deliver solutions, and the sub-Saharan African region, with a long projected population growth, will again be missing out on the potential benefits from expected advances in data-driven wheat yield resilience research.[54,55]

Opportunities for AI-Driven Innovations in Wheat Farming

We discussed the current state of wheat farming in Sub-Saharan Africa in terms of the dominant farming models being practiced and what is limiting the application of advanced technological solutions to enhance suitability given the emerging market prospects of wheat in the region. In the current section, we pinpoint key opportunities where artificial intelligence can be harnessed to drive real-world technological innovations for increasing wheat yields and resilience amidst rising climate and market threats. We do this in the context of the common wheat farming practices currently being implemented by smallholder farmers and the motivation informed by projected depleted nutrients, water resources, and altered weather patterns in the region. However, the majority of the invoked opportunities are general, and transfers can be realized across other crop-livestock systems and geographies. Specifically, among the smallholders, unleashing the wealth of data generation, analytical capabilities, and synthetic intelligence to inform not only the farmers but also public-private partnerships and policymakers is now even more imperative and needs to leverage the socio-economic and the newest technologies.[7,48,56,57]

Leveraging Artificial Intelligence for Enhancing Wheat Yield Resilience Amidst Climate Change in Sub-Saharan Africa. Climatic factors have been influencing wheat yields more acutely than the other cereals. Various industry sources continue to suggest that the adoption of artificial intelligence and machine learning are majorly shaping the next wave across sectors, including the agriculture sector, driving further growth in internet-of-farming, research, technical and remote sensing services, and the information and communication technology industry that are enabled by cloud computing. AI is being used to capture immediate feedback for enhancing plant breeding activities and selection of varieties with high yield potential, minimizing chemical use, soil fertility and nutrient management, immediate pest and disease control, farm machinery, and data-driven farming. Of all the major spurring sectors, actualizing AI-based solutions in the agricultural sector, more

https://doi.org/10.62486/latia202588 ISSN: 3046-403X

so with the smallholder farmers in Sub-Saharan Africa, has been thought to be particularly impactful in allowing for environmental sustainability goals excursions. The main reasoning for this comes from the nature of the farming activities and practices that these smallholder farmers engage in, as well as their socio-economic, socio-cultural, and geographical endowments.(58,59,60,61)

Precision Agriculture

Precision Agriculture Precision agriculture is an important application area of advanced technologies like AI in agriculture aimed at increasing crop yield, reducing farm management costs, and minimizing environmental impact. This area utilizes location-specific crop management, enabling farmers to make more appropriate decisions on crop management by ensuring that the effects of individual variations, small areas, and short passage times are considered. The main focus here is on maximizing yield, and the integration of crop input variations relies on data provided from all in-field variations. While the use of precision agriculture in cultivation is widespread in developed countries and greenhouse production, in sub-Saharan Africa and most developing countries, it is still in the research and exploratory phase. However, the increase in data available to researchers and policymakers in these countries is already pushing the traditional barriers to the adoption of precision agriculture practices. The recent increase in the availability of data, especially with the development of different types of drones, IoTs, and the use of satellite imagery and unmanned aerial vehicles for data collection, advances in big data analytics, and huge developments in global cloud services have improved the use of precision agriculture in developing countries. Precision agriculture technologies such as GPS guidance, auto-steering, and quality monitoring systems are becoming more accessible to farmers through cooperatives and contractors. Household-level results showed that patchwork utilization is associated with better maize yield performance; however, great variability in measured technology variables and limited access to public information represent barriers to the upgrade of site-specific technologies. With the integration of AI into precision agriculture, data analytics, decision support, and prediction models introduced can be used by farmers in developing countries to pinpoint location-specific and time-dependent pests, diseases, and soil management actions during farming.(62,63,64,65,66)

Climate Prediction and Adaptation

Climate prediction, also known as weather forecasting, is the application of science and technology to predict the state of the atmosphere for a future time and a given location. How the weather will evolve is predicted by simulating the atmosphere, including temperature, wind, and precipitation, using weather patterns with historical data. Data on the physical conditions that describe the climate—wind, temperature, humidity, and more—are continuously collected by meteorologists. Their observations are compiled in systems called databases and are used to forecast future weather or even to predict it. Weather forecasts are very important tools that help to prevent disasters associated with extreme weather, such as drought and heavy rainfall. For instance, when the probabilities are that a drought will occur, farmers are warned and can think about planting different varieties of plants that are more resistant to drought.(67,68,69,70,71,72,73,74)

Recommendations for Effective AI Implementation Iin SSA

A great deal has been invested in the development of digital technology in agriculture in recent years. Various principles have been derived and guidelines offered to ensure the responsible application of AI for sustainable and equitable development in meeting the Sustainable Development Goals. Challenges remain, however, in the interdisciplinary realization and uptake by practitioners of those principles. This especially applies to smallholders in developing countries. The following subsections discuss guidelines for the responsible implementation and uptake of AI to help elevate wheat yield resilience among smallholder farmers in SSA.

Data Strategy Guidelines for Advancing AI in SSA

It is widely acknowledged that data access, quality, and integration are key for successful development and deployment of agricultural AI. AI and data analytics were advanced as major solutions to achieve agricultural research for development impact in the decade 2017–2025; the Platform for Big Data in Agriculture is fostering and engaging in various AI-led initiatives in developing countries. Enabled by advanced digital collection tools and mobile phones, a proliferation of data-enabled agriculture promotion activities among civil society organizations, government, and the private sector has been observed, including those linked to gender and nutrition. Yet with all these advancements, smallholder farmers still face data challenges. High-quality, context-specific, and up-to-date data are scarce in developing countries where the majority of smallholders reside.

Policy and Regulatory Frameworks

AI applications have been and will continue to be regulated by both national and regional laws and rules. Therefore, there is a need to develop national and regional bodies that will regulate the application of AI in

https://doi.org/10.62486/latia202588 ISSN: 3046-403X

solving Africa's agricultural challenges. These bodies must have clear powers that will enable them to design the required regulation since the complexity of AI offers both opportunities and challenges for producers and consumers in the agricultural value chains of Africa. Already, there are global and regional organizations that are formulating and advising countries on property rights for both data and AI-generated outputs. In 2015, guidelines for the production and use of genetically modified organisms (GMOs) were adopted which could help in the regulation of AI. Although these guidelines do not expressly name GM crops, experimental development activities can be interpreted as those that involve genetic engineering, including gene editing and the use of AI.

Africa and most of the world consider the CRISPR-Cas9-based gene editing system as a GMO technology. Therefore, African countries should fast-track the formulation of AI policies and embed these within their regional and national agricultural policies. To facilitate this process, an expert group from the African Union and other regional bodies can be set up to develop a technical policy and regulatory framework and implementation plan for AI utilization in African agriculture.

To do this, there will be a need for AI systems that can generate knowledge relevant to local conditions and practices, demonstrate insights, and enable the development of AI knowledge and skills in various agricultural value chain stakeholders, including smallholder farmers. The policy and regulatory frameworks should comply with international standards and should adhere to principles on AI as well as values of responsible artificial intelligence. Also, the ability of AI-based and similar knowledge systems to address relevant privacy, transparency, and accountability challenges needs to be factored into the regulatory oversight. Finally, the unique needs and aspirations of Africa's agriculture and sustainable development should be reflected in the regulatory frameworks. This will place Africa on a path to addressing the future potential of AI in agriculture and sustainable development, and Africa will be positioned as a leader in adopting emerging technology advances that can enhance the continent's ability to realize its comprehensive sustainable development aspirations.

Capacity Building and Training

As the interdisciplinary training of AI experts and domain specialists is a key requirement for successful industry deployment of AI algorithms, we proactively engage and leverage undergraduate and postgraduate training students for long-term sustainable outcomes. The selection of eligible domestic and international students takes place annually, and extrinsic incentives such as fellowships are employed to increase market appeal. Machine learning and signal processing syllabi are streamlined, and course material such as lecture notes, tutorials, exercises, and examination papers are shared with the broader academic community. Selected students have the opportunity to co-observe in the delivery of annual national and international industry courses, which culminate in internationally recognized certifications. We also regularly conduct personalized boot camps, themed hackathons, and project days for encouragement and exposure to practical experience with the suggested concept.

Internships, project-based aid, summer jobs, apprenticeships, and similar arrangements support the interest of undergraduate students to pursue their practical training with us. We have good relationships with regional universities, especially our African partners, where we have appointed the AI track and the vice president of the education and training unit. We support several specific AI activities. In several African countries, where more than 50 % of the African population is younger than 25 years, our pipeline has been laid to reach high school students to grow emerging talent.

CONCLUSION

The integration of artificial intelligence (AI) in wheat farming presents a transformative approach to addressing climate change challenges and enhancing wheat yield resilience in Sub-Saharan Africa. AI-driven techniques, including deep learning models for non-destructive leaf area index assessment, convolutional neural networks for wheat lodging prediction, and machine learning for disease detection, significantly improve crop monitoring and management. These innovations provide data-driven insights that optimize breeding efforts, improve resource efficiency, and enhance overall agricultural sustainability. The ability to harness large-scale data through AI applications enables better prediction of environmental stressors, facilitating adaptive strategies for farmers in vulnerable regions. Despite its potential, AI adoption in wheat farming faces challenges, including limited infrastructure, data availability, and technological accessibility. Addressing these barriers requires a concerted effort in capacity building, investment in digital infrastructure, and the development of policy frameworks to support AI-driven agricultural innovation. By leveraging AI, Sub-Saharan Africa can bridge its wheat production gap, ensure food security, and promote climate-resilient farming systems. Future research should focus on refining AI models, enhancing accessibility for smallholder farmers, and integrating AI with sustainable agricultural practices to maximize its impact on wheat production in the region.

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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.

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Conceptualization: Fredrick Kayusi, Petros Chavula.
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