02. MODELS

Localized Agri-LLMs: Exploring Low-Power, Low-Cost Models for SSPs in Africa and India

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Abstract

The transformative potential of artificial intelligence (AI) in agriculture is increasingly recognized, yet most large language models (LLMs) remain inaccessible to small-scale producers (SSPs) in Africa and India due to high computational requirements, limited localization, and infrastructure constraints. Artificial intelligence in agriculture offers significant promise for smallholder farmers, agricultural extension systems, digital agriculture transformation, and agri-food system modernization; however, a widening gap persists between AI capability and real-world accessibility in low- and middle-income countries (LMICs). Most LLMs are designed for high-bandwidth environments, trained on non-representative datasets that poorly reflect African agriculture and Indian agriculture systems, and priced beyond the reach of agricultural extension agents, farmer organizations, and cooperatives serving SSPs, resulting in structural exclusion of smallholder farmers.

This paper examines the development and deployment of affordable, locally fine-tuned agricultural large language models (Agri-LLMs) for

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smallholder agriculture, agricultural advisory services, and digital extension systems through multi-stakeholder public-private partnerships integrated within agricultural extension systems and digital agriculture ecosystems. It reframes AI localization in agriculture as a systems-level challenge requiring alignment across AI model architecture, agricultural data governance, sustainable financing models, and policy frameworks.

It further explores localized, low-power, cost-efficient AI systems supporting climate-smart agriculture, precision agriculture, and farmer decision-support systems tailored to linguistic, cultural, and agronomic diversity in Africa and India, drawing on India's Digital Public Infrastructure (DPI) for agriculture and Africa's emerging agri-tech and AI innovation ecosystems.

1. Introduction

Small-scale producers (SSPs) are essential to agriculture, accounting for one-third of global food production and 84% of the world's agricultural holdings (Ritchie 2021). Their role is very important for food security and economic growth, especially in sub-Saharan Africa, where farming supports livelihoods and national economies. Given the challenges of extreme weather events that account for over 95% of Africa's rain-fed farms and weak extension systems, digital services offer powerful tools to address these and other challenges farmers face. In countries like Nigeria, SSPs produce up to 90% of the food consumed domestically (PWC 2020). In India, small and marginal farmers represent nearly 86% of all agricultural holdings (Gupta and Li 2021; Oxfam India 2022).

Despite their significance, SSPs struggle to access the technology and information needed to improve their productivity. Many farmers face challenges associated with technological infrastructure, language differences, and a lack of digital skills. This situation makes it hard for them to adopt modern farming practices to improve productivity.

Along the value chain, the knowledge gap remains a concern. Many agricultural extension agents, responsible for bridging the knowledge gaps of small-scale farmers, have little to moderate knowledge in the latest technologies, such as IoTs and Artificial Intelligence that could aid in decision-making, crop management, and sustainability efforts (Asante 2025). This situation limits both the reach and effectiveness of new agricultural innovations.

One-third of global food production comes from small-scale producers (SSPs), who struggle to access the technology and information needed to improve their productivity.

1.1 Problem Statement

Emerging technologies such as Artificial Intelligence (AI) present a scalable way to deliver agricultural information and support. Technologies like Large Language Models (LLMs) and computer vision have the potential to change how farmers access timely and relevant advice using natural language or visual inputs. These technologies support the creation of tools that understand local dialects and languages, making information easier to access for diverse rural communities (Yang et al. 2023; Almufareh et al. 2025).

Natural disasters such as extreme drought and flooding, intensified by climate change, have led to increased pest and disease infestations, threatening food security. AI-based innovations, combined with remote sensing, have contributed to climate-resilient agriculture by equipping farmers with data-driven insights to optimize resource allocation and planning (Pathania et al. 2025).

Even with existing technological innovations and advancements, many small-scale farmers remain excluded due to high costs, language barriers, and limited digital skills (Choruma et al. 2024). These challenges leave them marginalized and unable to access crucial agricultural information including diseases, climate and weather, and market data. Without intervention, these farmers risk falling further behind, threatening their livelihoods and local food security.

1.2 Aspirational Vision or Relevance

Given the threats posed by climate change and market fluctuations, empowering both small-scale farmers and their extension agents with cost-effective information dissemination channels and advisory companions tailored to their specific agricultural needs and regional contexts has become increasingly important. The vision of this discussion is straightforward and transformative, offering compelling value propositions for multiple stakeholders.

At the individual level, the efficiency and effectiveness of extension services can be optimized if local, in-country extension agents have per-user, low-cost access to low-powered, leading-edge LLMs specifically fine-tuned for small-scale producer contexts. This would fundamentally transform the advisory capacity of extension services, enable highly localized, real-time farming advice, and catalyze improvements in productivity, resilience, and sustainability among smallholders (Prestegaard-Wilson and Vitale 2024). At the same time, this vision presents a compelling opportunity for investors and innovators to deliver and scale affordable AI solutions tailored to small-scale producers. By making advanced AI both accessible and cost-effective, they can unlock new value for farmers, foster inclusive innovation, and drive sustainable growth across rural communities and the broader agricultural ecosystem.

1.3 Research Objectives

At a time when global food systems face increasing pressures, this paper advocates for AI solutions that address the core issues of accessibility, affordability, and contextual relevance. By enhancing the capacity of extension services, these solutions aim to ensure that critical agricultural knowledge reaches the small-scale producers who need it most. The paper aims to accelerate the much-needed collaboration among key stakeholders including governments, research institutions, technology developers, agricultural stakeholders, and donors on the responsible and equitable use of AI in agriculture. It highlights the current landscape, identifies emerging opportunities and persistent challenges, and frames key questions necessary to guide inclusive and sustainable innovation.

To move from aspiration to implementation, this discussion paper addresses four critical questions that are fundamental to realizing the vision of democratized agricultural AI:

- **Technical Implementation and Localization:** What technical considerations are required to effectively fine-tune and deploy LLMs for diverse small-scale producer contexts while maintaining quality, reliability, and relevance across different crops, climates, languages, and farming systems?
- **Economic Viability and Sustainability:** What sustainable business models and innovation pathways can enable technology providers to serve smallholders while delivering long-term value and avoiding digital exclusion?
- **Collaboration Framework and Ecosystem Development:** What partnership structures, governance models, and coordination mechanisms are needed to align technology developers, agricultural stakeholders, extension services, and investors around shared goals and sustainable implementation?
- **Ethical AI and Data Governance:** What data ownership rights, transparency measures, and accountability mechanisms are needed to ensure AI solutions in agriculture protect farmer interests, build user trust, and promote inclusive, responsible, and sustainable adoption?



2. The Current State of AI Technologies for Agriculture

The global agri-food sector is under growing pressure from rising populations, climate change, and resource limitations, all of which threaten food security (FAO 2025). These challenges are worsened by geopolitical events such as conflicts, supply chain issues, and funding cuts, making it harder to combat hunger (Oliveira and de Souza e Silva 2023). To address these issues, agriculture must shift from traditional practices to innovative solutions.

One of the most promising technologies is artificial intelligence (AI), which can transform how we grow, manage, and distribute food. In high-income countries, AI is already used for irrigation, disease detection, pest control, and yield prediction, offering a path toward food security. But what if similar AI innovations were accessible and affordable to farmers and delivery partners in low- and middle-income countries (LMICs)?

In Africa and Asia, innovation must go beyond high-tech tools; it should also empower women and youth, support community solutions, reflect linguistic diversity, and include social and financial innovations within the communities.

2.1 Global AI Landscape and Relevance for Agriculture

LLMs represent a major component of AI solutions across sectors including agriculture. LLMs are increasingly used for text summarization, translation, and advisory services (Brown et al. 2020; Chen and Huang 2024). Models like Bidirectional Encoder Representations from Transformers (BERT) and Generative Pre-trained Transformer (GPT) have become foundational models used for developing AI applications (Gon et al., 2024). ChatGPT and other advanced models have made AI more accessible (OpenAI 2023; OpenAI 2025). Other top companies like Anthropic, Meta, and Google have developed their own powerful models with features such as longer context windows and multimodal reasoning (Anthropic 2025; Google Cloud 2025).

Open-weight models, such as LLaMA, Mistral, and Falcon 7B have enabled low-cost deployments, while mixture-of-expert models like GLaM and DeepSeek and domain-specific models like Jurassic-1 and HyperCLOVA have further lowered costs and improved efficiencies, making it easier to build AI tools (Naveed et al. 2024).

Globally, Artificial Intelligence (AI) has become a strategic focus for governments, industries, and research institutions. Over 70 countries have launched national AI strategies on data privacy, ethics and innovation incentives. In regions like North America, Europe, and Asia, AI initiatives are often backed by major public-private investments and framed by robust policy ecosystems (OECD AI 2021). For example, in 2024 alone, U.S. companies invested $109.1 billion in AI, and the European Union passed the world's first comprehensive risk-based AI Act. China leads in AI patents and research output, while India stands out in South Asia for its inclusive AI infrastructure through its Digital Public Infrastructure (DPI), initiatives such as the Indian Digital Ecosystem for Agriculture (IDEA), Agristack, and BHASHINI (Beriya 2022; Stanford Human-Centered AI Index Report 2025).

However, these global advances often center on high-compute, high-resource environments, leaving a growing divide in terms of access, applicability, and inclusion for sectors like smallholder agriculture in low- and middle-income countries (LMICs). Africa, for instance, remains largely absent from global top rankings in AI investment and infrastructure. Although the African Union adopted a Continental AI Strategy in 2024, fewer than 20 countries on the continent have national AI policies in place (Intelpoint 2025; Research ICT Africa 2025).

This disparity underlines the need for localized, affordable, and context-aware AI models, especially in agriculture, where most producers are small-scale farmers with limited access to high-end infrastructure. As the global AI race accelerates, the challenge is not just catching up but adapting innovations to local realities through multilingual interfaces, open data standards, and inclusive policy frameworks.

2.2 Current Application of LLMs in Agriculture

Several global language models have been deployed and used in different areas to improve farm productivity, some of which are discussed below:

i. Supply-Chain and Demand Management

In the post-harvest and distribution areas, LLMs help connect demand forecasting, inventory, and logistics. They analyze various unstructured information like news articles, social media trends, and policy updates against sales data to create market summaries that can be easily understood by users. A user can ask about inventory

levels or storage utilization and receive concise, actionable insights. Using natural-language interaction with analytical modeling, LLMs promise to boost resilience and efficiency across agricultural supply chains (Menache et al. 2024).

Initiative Highlight:
OptiGuide: OptiGuide is a supply chain tool powered by a large language model (LLM) that makes decision-making easier for users by allowing them to ask plain-language 'what-if' questions and get fast, practical planning advice. The tool is available on GitHub and can be integrated into other applications to enhance decision intelligence capabilities.

ii. Crop Production

Large language models (LLMs) can transform different farm data on soil moisture, UAV imagery, satellite remote sensing, and smartphone field reports into coherent, actionable guidance. By interpreting natural-language prompts, LLMs generate precise irrigation and fertilization schedules, flag emerging pest or disease hotspots from image metadata, and draft tailored recommendations for harvest timing. When integrated with yield-prediction pipelines, LLMs can explain model outputs in context, helping agronomists refine planting and input-allocation strategies.

- **Pest and disease detection:** LLMs analyze outputs from computer vision models, such as leaf discoloration heatmaps or pest infestation counts, and generate prioritized treatment plans, automatically drafting robotic sprayer instructions or farmer-friendly alerts that summarize disease risk and recommend targeted fungicide, herbicide, or insecticide applications.
- **Yield prediction and big data integration:** By processing meteorological forecasts, satellite indices, and market-price histories, LLMs produce integrated yield forecasts alongside narrative insights and support interactive scenario queries, thereby helping farmers optimize input allocations and market strategies (Tan 2024).
- **Genomics:** LLMs integrate diverse genomic and phenotypic data to develop new models and best breeding recommendations on how to enhance flavor, nutrition, and crop resilience (Columbia University 2024).

Initiative Highlights:
SoyDNGP: a high-performing, user-friendly deep-learning toolkit for soybean trait prediction. It transforms raw genotype data into three-channel images that convolutional neural networks can analyze, delivering accurate forecasts of complex traits. The toolkit is available as a Python package, providing a solid foundation for researchers and developers to build upon and extend.

PlantVillage AI: was developed by Pennsylvania State University and IITA for crop disease detection. It has a chatbot for interactive conversations with users. The dataset used to train the model, which spans 14 crop species, is also hosted on GitHub. It serves as a valuable resource for innovators looking to develop similar models to address yield losses in crops caused by infectious diseases.

iii. Livestock Management

In modern barns, wearable and environmental IoT sensors produce rich time-series data on animal location, activity, temperature, and biometrics. LLMs transform these raw streams into natural-language health and behavior reports summarizing herd stress indicators, detecting early signs of illness, and recommending feeding or veterinary interventions.

Initiative Highlights:
CattleEye: a hardware-independent autonomous livestock monitoring platform. It uses a low-cost security camera to capture video footage and provide insights into your herd's health and productivity. These insights can be accessed via smartphone, tablet, or PC.

FarmPro: uses AI to turn smart ear-tag and weather data into clear health reports, early warning alerts, breeding tips and suggestions to keep herds healthy and productive. The application is available on the web, Android, and iOS.

2.3 Policy and Regulatory Frameworks

Africa lags behind other regions in terms of AI policy development, with less than ten countries (Algeria, Benin, Egypt, Libya, Nigeria, Rwanda, Senegal and Tunisia) having published their AI policies and strategies (Research ICT Africa 2025; Ozibo 2025). India, by contrast, does not yet have a comprehensive AI law but has released the "Responsible AI for All" strategy through NITI Aayog at the strategic level (NITI Aayog 2021). Key global AI strategies and frameworks shaping AI regulations across regions include the OECD AI Principles, emphasizing inclusive growth, transparency, and respect for human rights; the Council of Europe's Framework Convention on Artificial Intelligence and Human Rights, Democracy, and the Rule of Law; the EU AI Act, the first comprehensive risk-based AI law in a major economy; the African Union's Continental AI Strategy, outlining a united vision for ethical, responsible, and equitable AI development across member states; and the U.N. AI Advisory Body's report, which calls for coordinated collaboration among standards bodies, industry, civil society, and governments to manage AI-related risks.

Other policy frameworks include the Responsible AI Adoption for Social Impact (RAISE) initiative launched by Canada, which seeks to promote the equitable and ethical deployment of AI technologies for social good, and the Responsible AI Safety and Education Act enacted by New York State, which establishes uniform safety standards, mandates AI literacy programs, and requires transparency and accountability in both public- and private-sector AI applications.



3. Methodology

3.1 Identification of Relevant Journals and Articles

This research engaged a semi-systematic literature review approach for the identification of relevant research journals, papers, and case studies for the analysis using a PRISMA flow diagram (Page MJ, et al. 2021). We conducted a systematic search for journals published between January 2020 and July 2025, using keyword searches on academic databases and preprint servers. It focused on five thematic clusters: AI technologies (Artificial Intelligence, Machine Learning, LLMs, Generative AI); agricultural context (Agriculture, Digital Agriculture, Precision Farming); target users (Smallholder Farmers, Rural Communities, Extension Agents); adoption themes (Technology Adoption, Inclusion, Accessibility, Training); and geographic focus (Africa, Sub-Saharan Africa).

Meanwhile, keyword searches to identify all case study research articles published in journals are reported to be unreliable, according to State-of-the-Art: The Quality of Case Study Research in Innovation Management by Goffin et al., 2019. Therefore, an encompassing method adopted by Goffin et al. 2019 was used by manually browsing articles in reliable journals and key organizational websites. Relevant articles and reports were selected based on the relevance of their abstracts and full text to the study.

3.2 Data Sources

A total of 285 records were identified on the Google Scholar database, and after screening titles, abstracts, and full texts for relevance and eligibility, 67 publications (including 16 reports by organizations) were selected based on their relevance to the intersection of artificial intelligence, digital agriculture, and smallholder farming in low-resource settings, particularly in Africa.

Data sources include data from academic database servers (arXiv, IEEE, ScienceDirect, Agriculture (MDPI)) and organizational and policy websites (FAO, UN, OECD, EU, UNESCO, World Bank, Research ICT Africa, Columbia University, and Policy Vault).

Primary qualitative data were collected through key informant interviews with implementation partners from IITA, including PlantVillage Nuru and Akilimo. Informed verbal consent was given at the start of interviews. These interviews provided practitioner insights on adoption barriers, localization strategies, business models, and policy engagement, complementing the literature review and strengthening triangulation of findings.

3.3 Methods for Data Analysis

The methods employed for analysis in this study include:

- Multi-case analysis was used to analyze Theme II on Economic Viability and Sustainability. It assesses types of business models or incentives that would make it viable for innovators to develop and maintain fine-tuned AI for smallholder farmers in the long term.
- Analysis of independent research studies or literature was conducted for Themes I, III and IV on technical implementation, collaboration framework and ethical AI respectively.

4. Key Findings

4.1 Theme I: Technical Implementation and Localization

i. Barriers limiting small-scale agricultural producers and extension agents from accessing and utilizing AI tools

Despite the growing potential of AI across various industries, small-scale agricultural producers and extension agents in Africa face significant challenges in adopting AI for more efficient farming practices. These challenges primarily stem from three interconnected factors: limited technological infrastructure, inadequate data availability, and a persistent digital literacy and skills gap. The issues related to infrastructure and data are particularly relevant to investors and technical implementers of AI solutions, who often struggle with building and sustaining systems in regions with weak internet connectivity and limited datasets. On the other hand, challenges associated with digital literacy and skill are more acutely felt by individual smallholder farmers, who may lack the training and experience needed to engage with AI tools effectively, even when those tools are made available. Bridging these divides is crucial for the equitable and effective integration of AI into Africa's agricultural sector.

ii. Cost of Adoption

Implementation of AI solutions requires considerable financial investment from both technology providers and end-users. Existing free access to AI applications only offers limited features (Harish Babu and Reddy 2025). Deji et al. (2023) also noted high-cost barriers as a major impediment to the use of AI in agricultural extension services. This cost is often unbearable for small farmers and poses a significant economic impediment (Adebote et al. 2025).

iii. Technology Infrastructure

Many rural areas, and by extension, small-scale agricultural producers, are not able to access a reliable internet connection (Gikunda 2024). This poor connectivity limits the effective use of AI mobile applications and hinders real-time data transmission and continuous operation essential for AI systems. Relatedly, inadequate electricity supply and unreliable power are also significant challenges in these areas.

Findings from key informant interviews further indicate that limited smartphone ownership remains a major constraint, particularly among women and youth. Implementers have responded by prioritizing feature phone-compatible solutions, including interactive voice response (IVR) systems, USSD interfaces, pictorial guides, and offline applications delivered through extension networks.

iv. Data Availability

Implementation of AI for agriculture in Africa faces a data scarcity challenge that reduces the quality of AI-driven insights (Belgaid and Ennaji 2025). While Africa holds unique agronomic data, access is often restricted by fragmentation, privacy, and limited collection efforts (Azeez and Adeate 2024). This lack of local data hinders AI's potential in improving crop yields, as ML models trained on insufficient or skewed datasets may be biased or inaccurate.

Furthermore, existing climate research funding and AI development have often been concentrated outside these regions, leading to an over-reliance on Western-centric datasets that may not be applicable or transferable to the diverse environmental, cultural, and socio-economic conditions found locally (Mwale and Madiba 2024). Concerns about data privacy and security also complicate the collection and use of sensitive agricultural data, requiring robust data governance frameworks to build trust (Gikunda 2024).

v. Digital Literacy and Skill Gap

Smallholder farmers in rural regions frequently encounter challenges in adopting AI-based agricultural tools due to limited digital literacy and insufficient exposure to modern technologies, such as smartphones. This digital skill gap extends not only to farmers but also to local support networks and extension services, emphasizing the need for targeted training initiatives that address the specific requirements of the agricultural context (Oshikoya et al. 2025). This includes greater awareness of ethical AI considerations (Dara et al. 2022). Ozor et al. 2025 faced these challenges, including quality data access, reliable internet connection and smartphone literacy, in their participatory case study of adopting AI-driven solutions for pest and disease detection across Sub-Saharan Africa.

However, practitioner experiences show that voice interfaces, visual learning tools, and farmer-to-farmer extension models significantly improve adoption among low-literacy users. Champion farmers and peer learning networks have emerged as effective mechanisms for building trust and accelerating uptake.

vi. Considerations for Localizing Language Models for Agriculture

As LLMs demonstrate increasing utility in agricultural contexts, especially in advisory services, pest diagnostics, and market information services, their localization becomes essential to ensure relevance and effectiveness in smallholder systems. In the agricultural context, localization goes beyond language translation; it involves adapting AI to the sociocultural, ecological, and infrastructural realities of the environment where it is deployed. Here are some important considerations for localizing LLMs for agriculture:

Language and Dialect Integration

To ensure that AI serves the needs of agriculture equitably and effectively, language and dialect integration must be at the core of localization efforts. Across Africa and much of the Global South, smallholder farmers rely on a wide variety of local languages and dialects that are absent from mainstream AI datasets and technologies due to lack of documentation of indigenous languages (UNESCO 2025). For instance, about 32% of adults in Malawi cannot read or write at all (World Bank Group 2022). It is essential to invest in training models to properly handle the languages spoken in farming communities and also develop multimodal solutions that support speech.

When LLMs are designed to communicate in local languages, they do more than communicate technical advice; they help build trust and allow more people to access digital resources. Achieving this requires teamwork with local linguists, communities, and agriculture experts to capture the diverse voices of farmers (Samuel et al. 2025).

An example of a localized tool is **UlangiziAI**, which means "guidance" or "counseling" in Chichewa. The solution is an AI-powered agricultural advisory tool developed for Malawi by Opportunity International, a non-governmental organization. It responds to queries in either English or Chichewa, which is the native language of about half of the country's 20 million people (Wolfberg 2024).

India offers a comparable lesson through the BHASHINI initiative that hosts over 350 AI models that connect Indians to digital initiatives in their own language and create content in Indian languages.

Fine-Tuning Models for Local Agricultural Realities

General-purpose LLMs trained on large, global datasets often lack sensitivity to local agricultural conditions. This can result in irrelevant, inaccurate, or even harmful advice, so-called "hallucinations." To address this, contextual fine-tuning is essential. This process adapts the model to local realities by retraining it on datasets that reflect regional crops, soil types, climate patterns, and prevalent pests and diseases.

AgroLLM achieved a 93% accuracy rate in providing agricultural context-appropriate responses, outperforming generic models that rely solely on global data

Source: Samuel et al. 2025

For example, **AgroLLM** uses retrieval-augmented generation (RAG) to combine the strengths of LLMs with up-to-date, locally sourced agricultural databases. As a result, AgroLLM achieved a 93% accuracy rate in providing agricultural context-appropriate responses, outperforming generic models that rely solely on global data (Samuel et al. 2025).

Offline Access and Low-Power Tech

Many rural areas struggle with reliable internet and power. To make sure AI help is available, LLMs must work offline and on devices with low power usage, allowing farmers to use them on smartphones or simple hardware. This involves compressing models to run on low-power devices, enabling inference directly on smartphones, tablets, or rugged edge hardware. For example, Farm-LightSeek is a lightweight multimodal agricultural LLM system developed to run entirely offline, balancing performance and efficiency (Jiang et al. 2025). Edge computing and low-power solutions are opening up new opportunities for LLMs to access hyperlocal data resources and deliver timely insights to increase farming precision (Milvus 2025; Houston 2025).

Incorporating Indigenous Knowledge and Cultural Practices

Cultural bias and the lack of diversity in training data is a major problem of LLMs, resulting in general values becoming improperly embedded in models, which leads to misrepresentation (Johnson et al. 2022). Therefore,

for LLMs to truly resonate with smallholder farmers, they must reflect the knowledge systems, cultural values, and everyday realities of their users. This means acknowledging not just modern agricultural methods but also local techniques, remedies, and community norms that are often more trusted.

Digital Literacy and Interface

Many smallholder farmers and extension agents may be new to some AI tools (Asante 2025), which can make them hesitant. The way AI is presented matters a lot. Simple tools like WhatsApp chatbots or voice assistance can make it easier for those who aren't tech-savvy to use these resources. To maximize relevance and adoption, participatory design methodologies should be applied in designing national capacity building frameworks (FAO 2021).

Policy and Regulatory Fit

Finally, adapting LLMs to local context also means they need to fit into the laws and frameworks of the countries where they're used. This includes complying with regulations on data protection and aligning with national digital agriculture policies.

4.2 Theme II: Economic Viability and Sustainability

Our multi-case analysis reveals that digital agricultural AI tools in Africa employ diverse business models and incentives to drive adoption and long-term value creation. The findings, summarized in **Table 1**, highlight the diversity of models and various incentives used to drive both adoption and long-term value creation. **Table 2** provides additional lessons for sustainability with Indian case studies.

i. Analysis of viable business models or incentives for innovators to develop and maintain fine-tuned AI for smallholder farmers in Africa

Business models adopted by verified providers of local agricultural AI solutions identified by the African Development Bank's Technologies for African Agricultural Transformation initiative and other studies, as shown in Table 1, revealed the following:

- **Public-Private Partnerships (PPP):** Some digital agriculture AI providers depend on public-private partnerships (PPP) to offer services to farmers at the last mile. According to research by Omamo and Mills (2022), Africa requires an annual investment of US$76.7 billion (US$15.3 billion from the private sector and US$61.4 billion from the public sector) to transform its food systems and drive a sustainable shift in farming practices.
- **Free and Subsidized Access:** Many solutions (e.g. Akilimo, PlantVillage, Cassava Seed Tracker) rely on free or subsidized access for farmers, with funding from donors, government, or PPPs. Despite being free, the use of some digital agricultural tools like PlantVillage in rural communities is intricately linked to participation in awareness and training campaigns, receiving smartphones from project teams, and having contact with agricultural service providers (Adjéi Ettien et al. 2024). This highlights farmers' reliance on established agricultural support structures for effective technology adoption.
- **B2B/B2G Subscription Models:** Platforms like eProd operate on a business-to-business (B2B) or business-to-government (B2G) basis. Agribusinesses or government agencies pay for the onboarding, management, and analytics services, while access for farmers is provided at little or no cost. This model allows for scale, sustainability, and integration with public agricultural extension systems.
- **Non-Governmental Organization (NGO) or Philanthropy Model:** Open-access tools maintained by NGOs or universities (e.g., PlantVillage Nuru) are funded by grants and philanthropy. These models are sustainable only if long-term donor commitment or endowment funding is available.

India Context: Business Models for Sustainability

Government-led models in India like BHASHINI and KisanSarathi show how public investments in open infrastructure can drive innovation at scale. On the private sector side, startups such as CropIn, DeHaat, and Stellapps show how subscription and marketplace (B2B2C) models can complement DPI. Together, India cases reinforce the importance of combining government-backed infrastructure with market-driven models to achieve adoption, scale, and sustainability.

ii. Takeaways

As illustrated in Table 1, government support stands out as a key enabler for scaling digital agricultural tools and maximizing impact, especially in markets like Ethiopia (Case 4). The review finds that, in Case 5 (eProd), deploying the platform through group licensing to agribusinesses and governments, rather than individual

farmers, effectively reduces costs. Also, features such as offline functionality and SMS extensions help expand reach across under-connected regions.

In the India context, Table 2 reinforces this lesson. DPI models like KisanSarathi (extension) show how low-cost, inclusive government-led platforms can expand reach at national scale, while private innovators (CropIn, DeHaat, Stellapps) demonstrate how commercial sustainability can be achieved through B2B SaaS, marketplace, and subscriptions.

To achieve long-term value creation, policymakers should institutionalize reliable local tools within national extension and training programs. Funders should invest in capacity building for local talent and innovation hubs, while also encouraging innovators to lower per-farmer costs. Innovators, in turn, should adopt results-based business models that yield measurable impact and prioritize building robust data infrastructure, such as open APIs, to ensure accessibility.

Table 1. Summary of successful case studies of digital agricultural tools and agricultural AI providers, their business models, and impact in Africa.

Case	Digital Agriculture Provider	Country	Business Model	Incentives Used	Impact
1	**Cassava Seed Tracker** Developed by IITA	Nigeria, Tanzania	Free SaaS for seed certification; PPP	Donor, PPP, Government support	Tracked over 3,000 seed field certifications; localized in Nigeria.
2	**Akilimo** Developed by African Cassava Agronomy Initiative (ACAI) of IITA	Nigeria, Tanzania, Ghana	Free: Open-access digital advisory (mobile / Interactive Voice Channel / app / print / API); B2B partnerships	Donor support; partnerships with NGOs, private and public sectors.	Over 1.8 million farmers reached across Nigeria, Tanzania, and Ghana; over 441,000 hectares impacted; average 22% yield increase; and 70% of reached farmers applying recommendations, supported by a farmer-to-farmer extension model (Key Informant Interview, Author).
3	**PlantVillage Nuru** Developed by Penn State and localized with IITA and partners	Kenya, Tanzania	Free, NGO model Open-access library on crop health and AI disease diagnostics	Donor support/ Philanthropy	Nuru has increased yields by 30%, adding $300 annually to farmers' incomes. However, new research shows that the use of the PlantVillage application is closely linked to participation in training or awareness campaigns (Adjéi Ettien et al. 2024; Ahoya et al. 2024).
4	**NextGen Agroadvisory** Developed by Alliance Bioversity International – CIAT	Ethiopia	Free: Open-access digital advisory (AI/ML powered, API access)	Donor; partnership with Ethiopian government agriculture ministry and agencies; and international partners	According to the developer, the field validation shows wheat yield gains of 14% to 20% and net returns of up to USD 665 per hectare over conventional recommendations. Reaches more than 72,000 farmers; improves input-use efficiency and climate resilience; being integrated into the national extension framework and adaptable to other crops, countries, and agro-ecologies.

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Case	Digital Agriculture Provider	Country	Business Model	Incentives Used	Impact
5	**eProd** Developed by eProd Solutions Ltd	Benin, Burkina Faso, Cameroon, Côte d'Ivoire, DR Congo, Ethiopia, Ghana, Kenya, Madagascar, Malawi, Mali, Mozambique, Nigeria, Rwanda, Senegal, Uganda, Zambia, Zimbabwe	B2B/B2G Subscription Organizations or governments pay to onboard and manage groups of farmers.	Government adoption, client fees, partnerships	Used by 200+ clients and 350,000+ farmers across African countries; supports compliance (EU standards), SMS, and financial access; drives efficiency for governments and agribusinesses.

Source: AfDB Technologies for African Agricultural Transformation 2025; Adjéi Ettien et al. 2024; Ahoya et al. 2024.

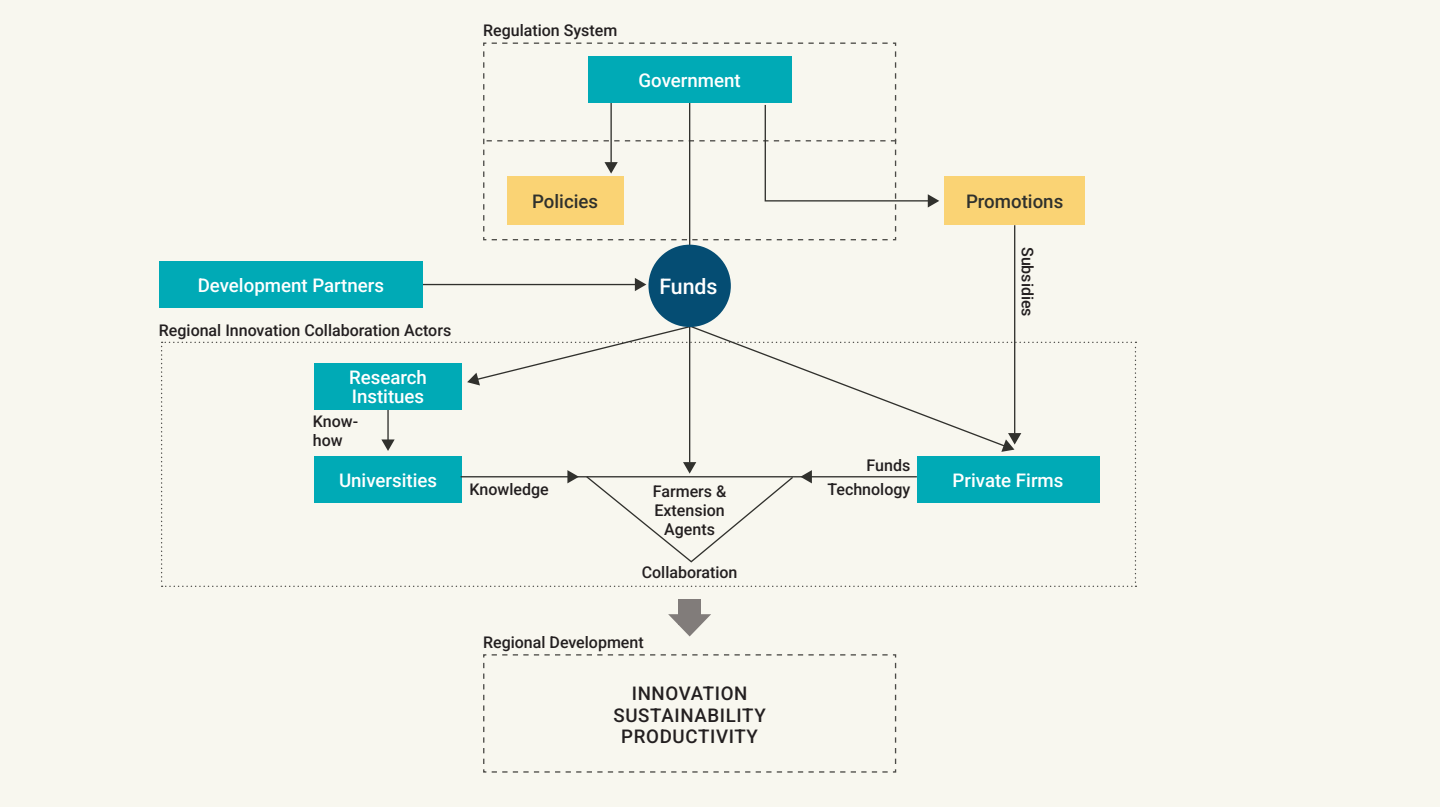
Table 2. Summary of successful case studies of digital agricultural tools and agricultural AI providers, their business models, and impact in India.

Case	Digital Agriculture Provider	Country	Business Model	Incentives Used	Impact
Government-led Digital Public Infrastructure (DPI) Initiatives					
1	**BHASHINI** Bhasha Interface for India	India	Free, open APIs for AI-powered language translation	Government funding; part of Digital Public Infrastructure (DPI)	Hosts 350+ AI models; supports startups and Indian languages.
2	**KisanSarathi**	India	Free digital advisory platform	Govt. program; ICAR & KVK network	–
Private AI / Digital Agritech Startups					
3	**CropIn**	India (operates globally)	B2B SaaS (acreage/ license model); Data-as-a-Service (Cropin Data Hub)	Enterprise clients, govt. contracts, donor projects	Digitized data across 10M+ acres.
4	**DeHaat**	India	B2B2C platform: Input sales + AI advisory + Market linkage	VC funding; partnerships with agri-input companies & Farmer Producer Organizations (FPOs).	Serves 2M+ farmers with crop advisory and market access.
5	**Stellapps**	India	B2B SaaS + IoT + AI platform for dairy	Venture-backed; partnerships with cooperatives, banks	Reaches over 2 million dairy farmers and 1 million animals; processes 11 million litres of milk per day through its platform; enables USD 3.4 million in farmer payments daily. Digitizes dairy productivity and supply chains.

Source: Author 2025.

4.3 Theme III: Collaboration Framework and Ecosystem Development for Agricultural Artificial Intelligence (AgAI)

Fig. 1: Multistakeholder Partnership Model of a successful agricultural ecosystem with innovative outcomes.



Source: Author 2025. Adapted and modified from Adamashvili et al. 2020.

i. Multi-stakeholder partnerships (MSPs) model for Agricultural Innovations

Shifting food systems towards digitalization requires modern strategies and frameworks that integrate emerging technologies such as artificial intelligence (AI). A 2020 study by Adamashvili et al. (2020) presented a "successful ecosystem for the agriculture sector" model that illustrates the interconnections among core actors and multi-stakeholders, including government, the private sector, research institutions, and farmers.

This model emphasizes the dynamic exchange of data, knowledge, and resources: governments set the regulatory and investment agenda, research institutions contribute expertise and innovation, private firms deliver technological solutions, and farmers serve as both adopters and beneficiaries. However, the model did not capture development partners and their roles from a global perspective. Therefore, we have reconstructed the model to show development partners' contributions to the African agricultural ecosystem illustrated in Fig. 1.

A recent case study of responsible AI frameworks in South Africa, Kenya and Ghana revealed the need for a more holistic approach to ensure AI is inclusive, sustainable and empowering for farmers and consumers that reflect the diversity of contexts in which farmers operate across the continent (Odhiambo 2024).

ii. Takeaways

The Multistakeholder Partnership Model illustrates a thriving agricultural ecosystem in which the government sets enabling policies and provides subsidies and funding that support research institutions, universities, and private firms. Development partners complement these efforts by supporting the implementation of sustainable programs. Farmers and extension agents are not merely recipients of AI technologies; they are central actors in the ecosystem, serving as both end-users and knowledge intermediaries

who ensure that innovations are grounded in local realities, practically applicable, and responsive to the evolving needs of farming communities.

Achieving lasting impact requires all stakeholders to work collaboratively to deliver relevant knowledge and technologies to farmers. Such coordinated efforts are essential for driving innovation, enhancing sustainability, and improving productivity across the agricultural sector.

4.4 Theme IV: Ethical AI and Data Governance

As we localize AI models for African agriculture, ethical design and governance are essential to protect farmer rights, ensure fairness, and avoid worsening existing inequalities.

i. Farmer Data Ownership and Sovereignty

Small-scale producers generate valuable agricultural data through interactions with advisory tools, mobile platforms, and smart farming technologies. Without clear governance frameworks, this data can be collected and monetized by technology providers without transparent consent or equitable returns. Ethical deployment of Artificial Intelligence (AI) in agriculture must reinforce farmer data sovereignty, ensuring that farmers have control over how their data is collected, used, and shared.

As of 2026, 43 out of 55 African countries have enacted data protection laws. 34 out of them have additionally established data protection authorities (Kirwa 2025). Countries such as Kenya and Nigeria have enacted general data protection laws, such as Kenya's Data Protection Act, 2019 and Nigeria's Data Protection Act, 2023, yet agriculture-specific guidelines are lacking. By contrast, India has also enacted the Digital Personal Data Protection (DPDP) Act 2023 which provides a baseline for privacy and consent in the country.

Combe and Camaréna 2024 highlight the need for comprehensive frameworks addressing technological, legal, and economic barriers, proposing models that integrate investment costs, potential commercial usage, and ecosystem service values. Such integrated approaches can foster trust, compliance, and sustainable data governance in agriculture.

Data privacy concerns can be addressed by governments establishing clear data policies and guidelines regarding data ownership, anonymization, and encryption of sensitive farmer information, along with farmer awareness programs to educate farmers about their rights and the implications of data sharing and technology use (Bhat et al. 2025).

ii. Algorithmic Transparency and Accountability

LLMs trained on biased data can produce misleading advice that can adversely affect marginalized groups and undermine user trust (Ranjan, Gupta, and Singh 2024). For smallholder farmers, this could result in poor planting recommendations, crop misdiagnosis, or unsuitable market strategies.

Therefore, algorithmic transparency is very important to ensure reliability and build trust with farmers (Karimian et al. 2022). Transparency processes like making model decisions explainable to users and auditable by external actors include documenting training datasets, disclosing limitations of model outputs,



As of 2026,

43 out of 55

African countries have enacted data protection laws

Source: Data Protection Africa

and establishing mechanisms for feedback and redress when errors occur. Models should also undergo regular bias audits, particularly to assess performance across different crops, geographies, and linguistic groups.

Algorithmic bias can be mitigated by training on diverse and inclusive datasets, conducting regular audits of AI systems for fairness, and developing explainable AI models with transparent decision-making processes that allow farmers to understand how conclusions are reached (Bhat et al. 2025). This requires partnerships between AI developers, agricultural researchers, and public sector regulators to co-design standards for accountability in digital agriculture systems.

Public Red Teaming strengthens these safeguards by enabling users from diverse backgrounds to interact with AI in real-world contexts, testing risks, vulnerabilities, and user impacts that technical reviews may overlook. As UNESCO's Red Teaming Artificial Intelligence for Social Good – The PLAYBOOK (Chowdhury et al. 2025) notes, this approach fosters more equitable and trustworthy AI systems.

iii. Youth and Gender-Inclusive AgAI

Women constitute nearly half of the agricultural labor force, yet they are reported to be less likely to adopt AI tools due to underrepresentation in both data and design processes for AI tools. Gender-blind technologies risk reinforcing barriers women already face in accessing land, finance, extension services, and decision-making roles.

On the other hand, youth, who are key agents of change and have the potential to drive technological adoption and modernization, are also increasingly disengaged from the sector (United Nations 2025). Challenges such as limited access to tailored digital tools, insufficient training, lack of incentives, and systemic exclusion from agricultural decision-making are contributing to a steady decline in youth involvement. Without deliberate efforts to include women, youth and persons living with disabilities in the design, deployment, and scaling of Ag-AI solutions, agricultural innovation systems risk losing the most important drivers of change in the sector.

Moutik (2025) introduces a new conceptual framework called the AI-Facilitated Gender Empowerment Ecosystem (AIGEE) model for developing inclusive and context-aware AI. The AIGEE model explicitly incorporates principles of intersectionality and feminist development, recognizing that not all women face the same barriers. It emphasizes that empowerment should be understood not only in economic terms but also through dimensions of agency, voice, and control over resources.

iv. Environmental Sustainability Considerations

Discussions about democratizing AI and making it accessible to all users must also consider the environmental sustainability of such initiatives. Deploying Agri-LLMs offline, in low-power modes and fine-tuned for local contexts, offers an environmentally friendly solution to support small-scale producers. Research has shown that smaller, domain-specific LLMs consume significantly less energy and produce lower carbon emissions during training compared to general-purpose LLMs (Singh et al. 2025). Moreover, the offline capabilities of these models reduce the need for constant cloud access, further lowering energy use and CO_2 emissions associated with cloud-based inference.

v. Takeaway

Establishing new policies that address data privacy concerns and enforce transparency is an important approach to gaining users' trust through the ethical and responsible use of AI, thereby encouraging adoption by farmers (Dara et al. 2022). This is achievable through participatory design, robust data governance policies, capacity building, and clear mechanisms for accountability (Onunga 2025), all of which ensure that AI tools are not only effective but also aligned with the needs and rights of end users. Involving youth and women farmers in participatory design fosters empowerment and ensures the AI addresses diverse gendered needs, supporting equitable outcomes.

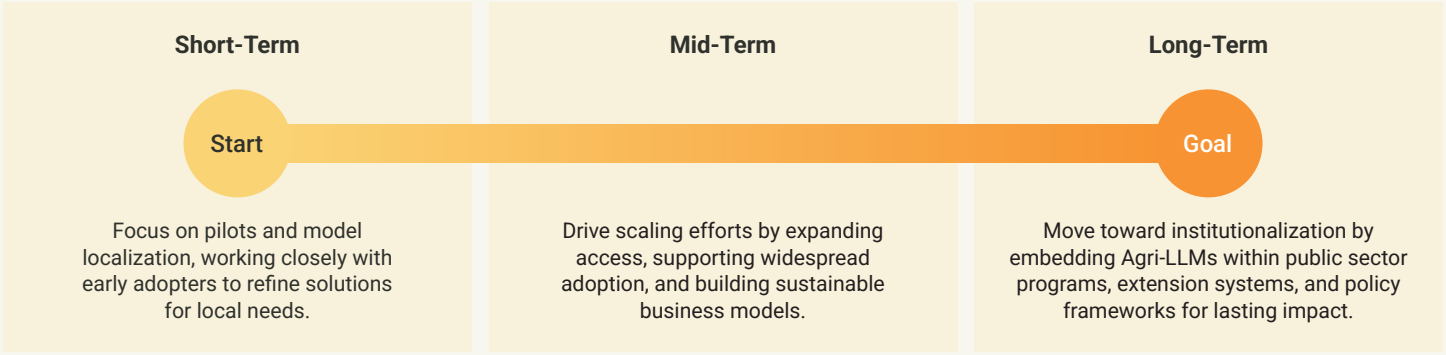


5. Final Thoughts / Reflections on Findings

Localizing Agri-LLMs in Africa and India requires that models be accessible, affordable, and contextually relevant. In Africa, this means improving infrastructure, digital literacy, and data availability; in India, it involves leveraging strong AI capacity and Digital Public Infrastructure (such as BHASHINI and Agristack) to bridge linguistic and regional divides. Governments and donors must incentivize innovators, while AI providers build sustainable business cases and deliver training with localized content. Future progress depends on strengthening partnerships, adapting standard AI policy, and investing in digital literacy and local data infrastructure.

To support this process, we propose a deployment and scale-up framework structured in three phases:

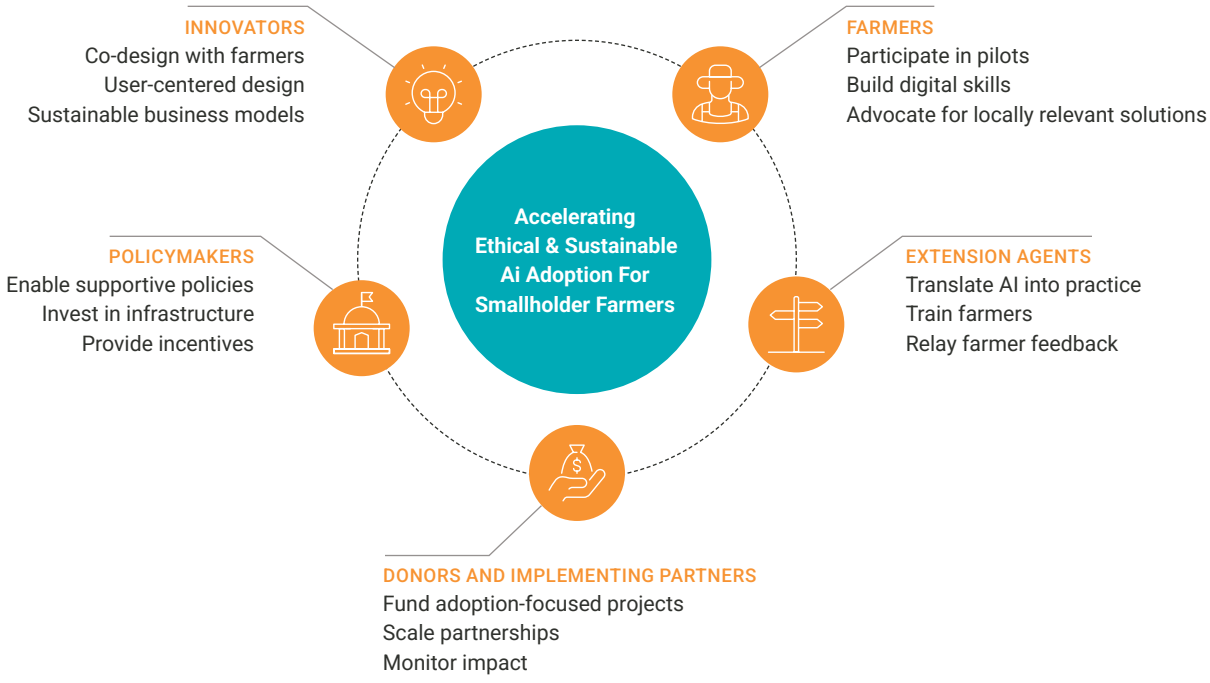
Fig. 2. Deployment and Scale-Up Pathway for Localized Agri-LLMs and Digital Agriculture Solutions



Recommendations

Sustained adoption of AI in agriculture requires a coordinated ecosystem approach that aligns innovation, delivery systems, policy frameworks, and financing to ensure solutions are practical, accessible, and scalable.

Fig. 3. Actionable Recommendations for Stakeholders for Sustainable Innovation in the Agricultural Ecosystem



i. Innovators

- Engage directly with rural farmers and extension agents at all stages of AI tool development to ensure solutions are locally relevant and designed for real-world adoption and use.
- Prioritize user-centered, intuitive design that accommodates varying digital literacy levels and infrastructural limitations, thereby reducing adoption barriers in low-resource settings.
- Develop and implement sustainable business models such as B2B or B2G, NGO partnerships, and public-private collaborations to enhance the accessibility and uptake of AI tools among smallholder farmers.

ii. Extension Agents

- Act as essential intermediaries by translating technical innovations into practical, easy-to-understand guidance that supports farmer adoption and use of AI-enabled tools.
- Lead capacity-building initiatives, such as digital literacy training and hands-on demonstrations, to empower farmers and facilitate widespread adoption at the community level.
- Create systematic channels for collecting farmer feedback and communicating adoption challenges to innovators and policymakers, thus ensuring continuous improvement and contextual adaptation of technologies.

iii. Farmers

- Participate proactively in pilot programs, testing, and feedback sessions to ensure AI solutions are shaped by real user needs and to accelerate adoption across communities.
- Engage in training and capacity-building activities to build digital confidence, enabling more effective and sustained adoption of new technologies.
- Advocate for solutions that are aligned with local languages, cultural norms, and traditional knowledge, strengthening ownership and likelihood of adoption.

iv. Policymakers

- Formulate and enforce policies and regulations that specifically facilitate the ethical, equitable, and safe adoption of AI technologies in agriculture.
- Invest in digital public infrastructure and extension services to systematically lower barriers to adoption, particularly in underserved rural areas.
- Provide incentives and remove regulatory hurdles to encourage the adoption of localized digital agriculture solutions by both private actors and smallholder farmers.

v. Donors and Implementing Partners

- Prioritize funding for projects with clear strategies to drive adoption and demonstrable livelihood improvements for smallholder farmers.
- Support multi-stakeholder partnerships focused on coordinated outreach and scaling of solutions to ensure adoption is sustained.
- Invest in business models and scaling approaches that facilitate adoption, financial viability, and long-term sustainability.
- Integrate comprehensive monitoring, evaluation, and learning systems to track adoption metrics, understand barriers, and inform adaptive strategies for maximizing adoption and impact.

AI Disclosure Statement

The authors acknowledge the use of NotebookLM and ChatGPT-4 as editorial support tools during manuscript preparation. The authors developed the initial ideas, arguments, and substantive content, while these tools were used to support language refinement, improve the coherence and structure of existing text, and enhance section-level flow. Their use was based solely on materials and content provided by the authors and was limited to editorial and structural support. Neither tool was used to generate or synthesize research data, results, findings, conclusions, figures, or literature citations, nor to generate substantive manuscript content. All AI-assisted revisions were reviewed and verified by the authors, who retain full responsibility for the accuracy, originality, interpretation, and integrity of the manuscript.

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ANNEX

Local Agri-LLM Initiatives

A growing number of AI-driven tools are currently in use across Africa and India to support small-scale producers (SSPs), extension agents, and agribusinesses. Below is a selection of notable tools and platforms:

AgNext	AgriBazaar	AgUnity
agnext.com **Country(ies):** India **Function:** Quality assessment of crops and produce.	agribazaar.com **Country(ies):** India **Function:** Digital trading and price discovery platform.	agunity.com **Country(ies):** Kenya, Uganda, Ghana, Ivory Coast **Function:** Digital recordkeeping for small farmers
Akilimo	**Amini**	**BHASHINI (Bhasha Interface for India)**
akilimo.org/ **Country(ies):** Nigeria, Tanzania, Ghana **Function:** AI-driven cassava agronomy advisory (fertilizer, planting & weed control) by IITA-ACAI	amini.ai **Country(ies):** Kenya **Function:** AI-powered satellite analytics for crop insurance and climate risk insights	bhashini.gov.in **Country(ies):** India **Function:** Multilingual AI translation platform enabling digital access for farmers.
CropCura	**CropIn**	**DeHaat**
cropcura.com **Country(ies):** Nigeria **Function:** AI-powered crop pest & disease detection with organic treatment recommendations	cropin.com **Country(ies):** Kenya **Function:** Farm digitization and yield prediction	agrevolution.in **Country(ies):** India **Function:** Crop advisory, inputs, finance, and market linkages.
eLocust3m	**eNAM (National Agriculture Market)**	**Farmer.Chat**
fao.org/locusts **Region:** Horn of Africa **Function:** Locust monitoring & early warning system	enam.gov.in **Country(ies):** India **Function:** Digital marketplace for transparent agri-trade.	farmer.chat **Country(ies):** Kenya, Nigeria, Uganda **Function:** AI support for extension workers and farmers
FarmSpeak	**Gooey.AI**	**Hello Tractor**
farmspeak.net **Country(ies):** Nigeria **Function:** Voice assistant & poultry farm management	gooey.ai **Region:** Global **Function:** Low-code platform for building multilingual AI WhatsApp & voice bots for farmers	hellotractor.com **Country(ies):** Nigeria, Kenya, Uganda **Function:** Predictive maintenance & tractor booking

iShamba	KisanSarathi	M-Shamba
ishamba.com **Country(ies):** Kenya **Function:** SMS-based farming advice and weather updates	icar.org.in **Country(ies):** India **Function:** Real-time digital advisory for farmers via ICAR and KVK network.	m-shamba.net **Country(ies):** Kenya **Function:** Data-driven farm management and advisory
Plantix	**SatSure**	**Shamba Pride**
plantix.net **Country(ies):** India **Function:** Crop disease diagnosis via image recognition.	satsure.co **Country(ies):** India **Function:** Satellite analytics for agri-insurance and risk mapping.	shambapride.com **Country(ies):** Kenya **Function:** Tech-powered Digishops with farm inputs and services
SOWIT	**Stellapps**	**UjuziKilimo**
Country(ies): Kenya, Ivory Coast, Senegal, Morocco & Tunisia **Function:** AI for irrigation and crop monitoring	stellapps.com **Country(ies):** India **Function:** Dairy traceability and productivity monitoring	ujuzikilimo.com **Country(ies):** Kenya **Function:** AI & sensors for soil testing and precision advice
Velociti	**Viamo**	**Virtual Agronomist (iSDA)**
velociti.io **Country(ies):** Ghana **Function:** Market and finance access powered by AI	viamo.io **Region:** Sub-Saharan Africa **Function:** Voice-based AI for non-internet users	isda-africa.com **Region:** Africa **Function:** AI-based soil and crop advisory via WhatsApp

AGX AI is a collaborative initiative led by DevGlobal, Dev-Afrique and Athena Infonomics, to accelerate the responsible design, development, and delivery of generative AI tools and services for small-scale producers (SSPs) in Africa and Asia. Funded by the Gates Foundation, the project builds a vibrant, aligned community to ensure that AI serves the people who grow the world's food.

agx.community/agx-ai