



Harnessing Artificial Intelligence for Agricultural Transformation

In Partnership with



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List of Acronyms

ACRE	Agriculture and Climate Risk Enterprise
ADENs	Agricultural Data Exchange Nodes
ADT	Agricultural Development Trust
AEZ	Agro-Ecological Zones
AI	Artificial Intelligence
AICCRA	Accelerating CGIAR Climate Research in Africa
AIEP	Agricultural Information Exchange Program
AGROVOC	Agricultural Vocabulary (by FAO)
AGRIS	International System for Agricultural Science and Technology
API	Application Programming Interface
BLS	Brown Leaf Spot
BMZ	Federal Ministry for Economic Cooperation and Development (Germany)
CBSD	Cassava Brown Streak Disease
CIMMYT	International Maize and Wheat Improvement Center
CMD	Cassava Mosaic Disease
CNNs	Convolutional Neural Networks
CoW	Coalition of the Willing
CSA	Climate Smart Agriculture
DPI	Digital Public Infrastructure
DST	Decision Support Tool
DSS	Decision Support Systems
DSSAT	Decision Support System for Agroecology Transfer
EIAR	Ethiopian Institute of Agricultural Research
ESA	European Space Agency
ETL	Extraction, Transformation, and Loading
FAIR	Findable, Accessible, Interoperable, and Reusable
FAO	Food and Agriculture Organization (of the UN)
FLOPs	Floating-point Operations Per Second
FSSAI	Food Safety and Standards Authority of India
GANs	Generative Adversarial Networks
GAEZ	Global Agro-Ecological Zones
GenAI	Generative Artificial Intelligence
GIS	Geographic Information System

GIZ	Deutsche Gesellschaft für Internationale Zusammenarbeit
GloMIP	Global Market Intelligence Platform
GPT	Generative Pre-trained Transformer
GPS	Global Positioning System
GSMA	GSM Association (mobile network industry org)
HACCP	Hazard Analysis and Critical Control Points
IBM	International Business Machines Corporation
ICRISAT	International Crops Research Institute for the Semi-Arid Tropics
ICT4Ag	Information and Communication Technologies for Agriculture
IoT	Internet of Things
IRRI	International Rice Research Institute
ISO	International Organization for Standardization
IVR	Interactive Voice Response
KIAMIS	Kenya's Integrated Agriculture Management Information System
LMICs	Low and Middle-Income Countries
LLMs	Large Language Models
MEQ Camera	Marbling and Eye Muscle Quality Camera
MFIs	Microfinance Institutions
ML	Machine Learning
MUIIS	Market-led, User-owned ICT4Ag-Enabled Information Service
NDVI	Normalized Difference Vegetation Index
NGO	Non-Governmental Organization
NLP	Natural Language Processing
NOAA	National Oceanic and Atmospheric Administration
NLMs	Natural Language Models
PPPs	Public-Private Partnerships
QR	Quick Response (codes)
QUEFTS	QUantitative Evaluation of the Fertility of Tropical Soils
RAG	Retrieval-Augmented Generation
RL	Reinforcement Learning
RNNs	Recurrent Neural Networks
SDGs	Sustainable Development Goals
SHGs	Self-Help Groups
SSA	Sub-Saharan Africa
SSHI	Supporting Soil Health Initiatives
SSPs	Small-Scale Producers

TC 347	Technical Committee 347 (ISO committee for IoT in agriculture)
TAMSAT	Tropical Applications of Meteorology using Satellite and Ground-based Observations
ULI	Unified Lending Interface
UP	Uttar Pradesh (Indian State)
VERs	Verified Emission Removals
XAI	Explainable Artificial Intelligence
YOLO	You Only Look Once (real-time object detection algorithm)

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Executive Summary

The global agrifood system stands at a critical inflection point. Climate shocks, rising input costs, fragile supply chains, and widening inequality are placing unprecedented pressure on food production and distribution. Small-scale producers (SSPs), who produce one-third of the world's food, are especially vulnerable. Artificial Intelligence (AI) presents a timely and powerful tool to help reimagine agricultural transformation in ways that are more productive, sustainable, and inclusive.

This report - produced by the World Bank's Agriculture and Food Global Practice with global partners - presents a comprehensive and development-oriented analysis of how AI can be responsibly deployed across agrifood systems, especially in low- and middle-income countries (LMICs). It moves beyond hype to deliver a grounded roadmap of applications, prerequisites, and investment priorities, while emphasizing ethical, inclusive, and scalable use.

What makes this report different?

- **A Systems-Level View Anchored in Development Goals:** While many AI-agriculture reports focus on technological potential or showcase startups, this report grounds AI in the broader developmental context of food systems transformation, emphasizing public policy goals: climate resilience, food security, inclusion, and sustainability. Additionally, it addresses foundational infrastructure such as energy and data governance alongside AI use cases.
- **LMIC-Centric with Scalable Case Studies:** This work prioritizes the unique constraints and opportunities in LMICs, such as energy deficits, the digital divide, and limited human capital, while underscoring the strategic relevance of AI in addressing these challenges. A compendium of more than 60 case studies has been curated to demonstrate the adaptability of AI across diverse sociopolitical contexts, with a strong emphasis on the role of public-private partnerships in driving scalable and sustainable innovation.
- **Emphasis on Digital Public Infrastructure (DPI):** The report makes a critical conceptual leap by framing DPI (for example, digital ID, land registries, and data exchange networks) as one of the enabling substrates for scalable AI. This integration of AI and DPI is a unique proposition, positing that AI will not scale inclusively without foundational digital infrastructure that is publicly governed and equitably accessible.
- **Responsible and Inclusive AI Deployment:** This report goes beyond technical feasibility

to examine ethical and governance dimensions. It identifies risks related to bias, privacy, and environmental sustainability and calls for localized, transparent, and inclusive AI practices, especially given the dominance of models trained on data from high-income countries.

What's different about AI now?

AI is not new—but its capabilities, accessibility, and societal relevance have changed dramatically due to two key developments:

- **The Rise of Generative AI (GenAI):** GenAI models can synthesize insights from massive unstructured datasets—text, satellite imagery, and audio—to support natural language advisories, local language interfaces, and synthetic data generation. This opens new possibilities for non-literate or low-connectivity user groups.
- **Multimodal Integration:** Agriculture is uniquely suited for AI because it generates diverse data types—images, climate records, sensor outputs, and more. AI models can now fuse this data to generate granular, predictive insights for input optimization, climate resilience, and market linkages.

Use Cases Highlighted

The report identifies high-impact AI use cases spanning the entire agrifood value chain, illustrating the strategic relevance and practical adaptability of AI across diverse LMIC contexts. These include:

- **Crop & Livestock Discovery** – accelerating research and development (R&D) through the identification of climate-resilient gene varieties and optimized breeding strategies.
- **Advisory & Farm Management** – enabling data-driven decisions via AI-powered pest diagnostics, precision farming tools, and real-time soil monitoring.
- **Markets, Distribution & Logistics** – improving market transparency and reducing spoilage with AI-enabled traceability, price forecasting, and smart contracts.
- **Inclusive Finance & Risk Mitigation** – expanding financial access through alternative credit scoring and climate-indexed insurance models.
- **Cross-cutting Applications** – supporting adaptive planning through synthetic data, agro-ecological zoning, and granular weather prediction.

Together, these innovations offer transformational potential—accelerating scientific discovery,

optimizing the use of scarce inputs, boosting productivity, improving food quality and market access, and strengthening environmental and climate resilience across agricultural systems.

Implications for Policy and the Future

As AI reshapes agriculture, policymakers must address five pivotal areas:

- **Data Sovereignty and Ethics:** Create legal frameworks that recognize farmers' ownership of agricultural data and mandate transparent AI algorithms with localized training datasets.
- **Energy and Connectivity Infrastructure:** Incentivize renewable-powered data centers and 5G or edge computing solutions in rural areas to bridge the digital divide.
- **Digital Literacy and Human Capital:** Invest in context-specific digital training for both farmers and local tech intermediaries. Human-centered design is critical for adoption.
- **Public-Private Governance:** Build PPPs that ensure AI solutions reflect local priorities, avoid vendor lock-in (where dependence on a specific company's technology makes it difficult or costly to switch providers), and balance commercial viability with public interest.
- **Environmental Sustainability:** Evaluate and manage the environmental footprint of AI compute and promote AI models that support regenerative agriculture.

Navigating Risks and Setting Strategic Priorities

AI offers transformative potential, but it is not a universal solution. Not every problem in agriculture requires AI, and not all AI investments will deliver equitable returns. Strategic deployment requires clear-eyed cost-benefit analysis, identifying where AI adds distinctive value—such as in processing unstructured data at scale, enabling predictive insights, or personalizing services in low-connectivity environments. In many contexts, simpler digital tools, better data governance, or improved institutions may yield more immediate and sustainable impact.

Equally important is the need to manage risks. AI systems, if poorly designed or unaccountably deployed, can reinforce inequalities, replicate biases, undermine privacy, and impose environmental burdens. LMICs face vulnerabilities given limited regulatory capacity, underrepresentation in global datasets, and unequal access to computing infrastructure. Inclusive governance, locally relevant datasets, and strong public oversight will be essential to ensure that AI deployment in agriculture advances—not undermines—development goals.

Recommendations

For Policymakers:

- **Adopt National AI Strategies** inclusive of agriculture, with clear implementation pathways and budgets.
- **Embed AI in AgriFood System Policy** by linking it to resilience, climate adaptation, and nutrition security goals.
- **Foster Open and Interoperable Data Ecosystems** by supporting Agricultural Data Exchange Nodes (ADENs) and FAIR data principles.

For International Development Institutions:

- **Integrate DPI and AI Investments** in agriculture projects, ensuring that identity, payments, and data infrastructures are AI-ready.
- **Support AI Readiness Assessments** and policy diagnostics for LMIC governments, especially in fragile or climate-vulnerable regions.
- **Channel Research Funding** to co-develop LMIC-relevant AI models with local institutions, focusing on crops, languages, and supply chains underrepresented in global models.

For Operational Teams:

- **Pilot AI Solutions in Anchor Use Cases** such as pest diagnosis, microinsurance underwriting, and advisory services, with embedded monitoring and learning frameworks.
- **Prioritize Interoperability and Modularity** in tech choices to avoid future fragmentation.
- **Engage Farmers and Extension Workers Early** to ensure solutions are user-centered and culturally grounded.

AI can be the engine of a new agricultural revolution - one that is digital, inclusive, and sustainable. But realizing this vision will require discernment: deploying AI where it offers true strategic value, and resisting hype where simpler, more appropriate solutions suffice. With the right investments in infrastructure, governance, and capacity, and a commitment to inclusion and ethics, AI can help reshape agrifood systems for the better. This report provides a practical blueprint for that transformation - placing LMIC farmers at the center of the AI era, and aligning innovation with equity, resilience, and public good.

01 Why Artificial Intelligence for Agriculture Sector



The global agrifood system stands at a critical crossroads, confronting unprecedented challenges that demand innovative solutions. Since 2020, global food insecurity has doubled to more than 300 million people, while agricultural production continues to battle an unyielding barrage of climate change-related hazards and disasters.¹

¹ WFP at a Glance, March 2025

These challenges disproportionately impact vulnerable populations, including small-scale producers (SSP) who produce one-third of the world's food². Simultaneously, our current agrifood systems exacerbate the climate crisis through land degradation, unsustainable farming practices, and inefficient supply chains. The projected global population growth to nearly 10 billion by 2050 places significant pressure on the agricultural sector to increase crop production and maximize yields, requiring either expanding land use or embracing innovative practices to enhance productivity on existing farmland.³ According to the Food and Agriculture Organization of the United Nations (FAO), agrifood systems contribute to around 31 percent of the world's carbon footprint.⁴ These pressing challenges necessitate transformative approaches that can navigate the complex interplay of food security, environmental sustainability, and economic viability.

Artificial Intelligence (AI) has emerged as a powerful catalyst for addressing these multifaceted challenges in the agrifood sector. The transformative promise of AI for sustainable development is increasingly recognized; UN Secretary-General António Guterres noted that "The transformative potential of AI for good is difficult even to grasp."⁵ In recent years, the agricultural landscape has witnessed remarkable AI-driven innovations that demonstrate significant potential to enhance productivity, sustainability, and resilience. From precision farming to livestock management, AI-powered tools are revolutionizing farming operations by optimizing resource use and reducing environmental impacts. This technological evolution represents a fundamental shift in how agricultural systems operate, and it offers unprecedented opportunities to address the pressing challenges facing global food security.

The strategic importance of AI in addressing these challenges is reflected in the substantial increase in national AI strategies worldwide. In 2017, only a handful of nations had released national AI strategies, but by 2023, most countries had either released or were in the process of developing such strategies (figure 1.1).⁶ This shift represents a growing global commitment to harness AI's capabilities across various sectors, including. The economic significance of this shift is further underscored by market growth projections; the global AI in the Agricultural market valued at US\$1.5 billion in 2023 is expected to grow at a compound annual growth rate (CAGR) of 24.5 percent to reach an estimated US\$10.2 billion by 2032.⁷

2 Lowler, Sanchez, and Bertini (2001), <https://www.fao.org/newsroom/detail/Small-family-farmers-produce-a-third-of-the-world-s-food/en>

3 World's population will reach nearly 10 billion by 2050, July 2019

4 Tubiello et al. (2022), <https://news.un.org/en/story/2021/11/1105172>

5 UNU (2024), <https://unu.edu/article/artificial-intelligence-can-transform-global-food-security-and-climate-action>

6 AI Index (2024), [OurWorldInData.org/artificial-intelligence](https://www.ourworldindata.org/artificial-intelligence)

7 AI in Agriculture Market, April 2024

Figure 1.1 Countries with National AI Strategies, 2017 and 2023*



Source: Data based on AI Index 2024; map based on [OurWorldinData.org/artificial-intelligence](https://ourworldindata.org/artificial-intelligence)

Note: Does not include broader innovation or digital strategy documents that do not focus predominantly on AI

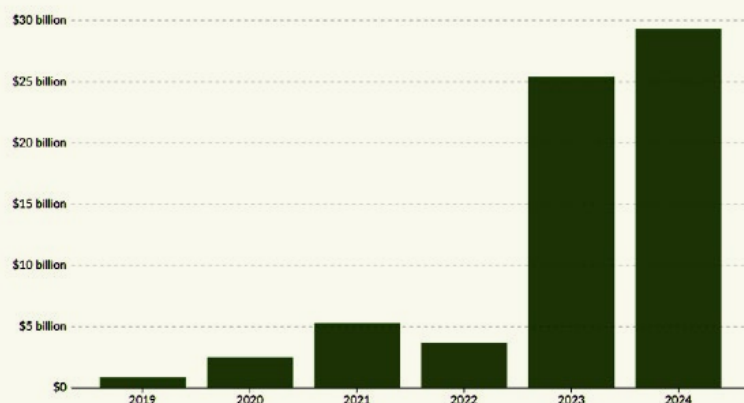
*The boundaries and names shown on this map do not imply official endorsement or acceptance

This promise of AI has been further amplified by the advent of Generative AI (GenAI) that represents a paradigm shift in accessibility and capability, with potential benefits for SSPs. Unlike traditional analytical AI, which typically solves specific tasks by making predictions based on well-structured data sets and predefined rules (such as forecasting yields or identifying diseases based on clear parameters), GenAI can generate new content by identifying patterns in massive unstructured datasets. This ability is particularly valuable for complex agricultural tasks that involve diverse data types, including images (satellite imagery, plant disease photographs), text (crop research papers, weather reports), and various sensor data (soil parameters, temperature readings).⁸ Natural language voice interfaces, conversational decision support, and visual tools are helping overcome numerous barriers to adoption that have traditionally limited technology uptake among SSPs. Global investment in GenAI has skyrocketed from less than US\$5 billion in 2019 to more than US\$29 billion in 2024,⁹ highlighting the increasing recognition of GenAI's potential to revolutionize industries and drive innovation (figure 1.2).

⁸ [author] (2024), <https://www.unite.ai/harvesting-intelligence-how-generative-ai-is-transforming-agriculture/>

⁹ Stanford HAI (2025), <https://hai.stanford.edu/ai-index>

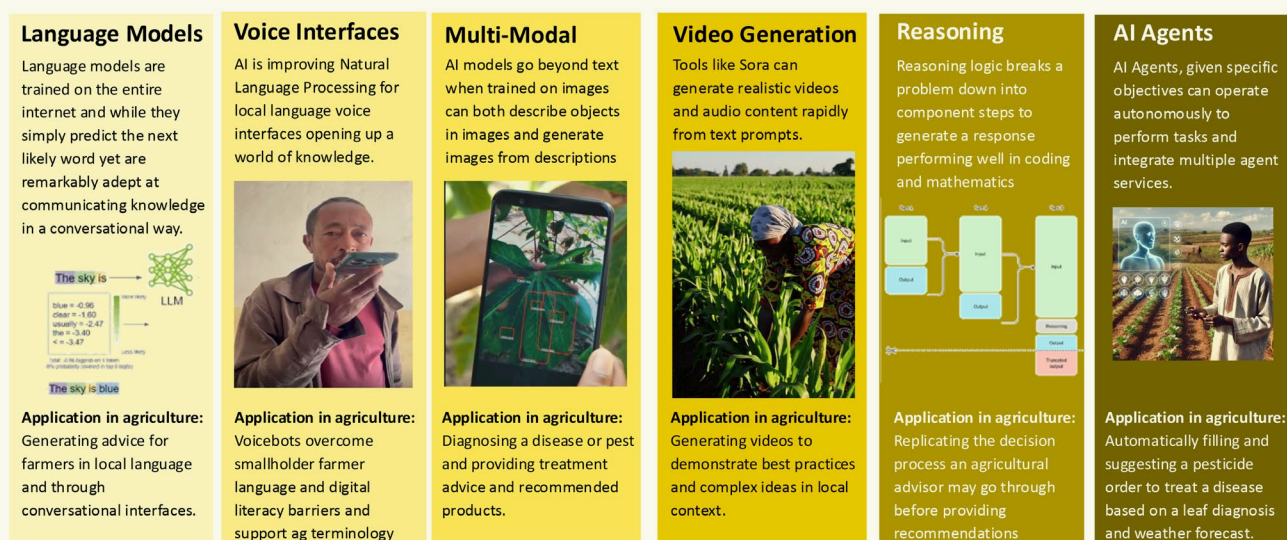
Figure 1.2. Global Investments in Generative AI, 2019 and 2023



Source: Data based on Quid via AI Index Report 2025; U.S. Bureau of Labor Statistics 2025; OurWorldInData.org/artificial-intelligence

The relevance of GenAI to agriculture is particularly significant due to the sector's inherently multi-modal nature. Agriculture is well suited for transformation by AI because of its high volumes of unstructured data, significant reliance on labor, complex supply chain logistics, and long research and development (R&D) cycles, as well as the sheer number of farmers that values customized offers and low-cost services. As an example, GenAI can develop testing scenarios by synthesizing millions of data points on weather, soil conditions, and pest and disease pressure; and analytical AI models can then simulate those scenarios. Using both technologies in tandem has the potential to increase efficiencies, lower costs, and improve environmental impacts for all stakeholders.

Figure 1.3. Key Generative AI Capabilities and Their Applications



Source: Gates Foundation (2025)

Across the agrifood system, several high-leverage application domains have emerged where AI offers unique advantages:

1. Synthesizing Multimodal, Unstructured Data: Agriculture generates vast and diverse data streams, from satellite images and audio clips to handwritten records and sensor feeds. AI, particularly deep learning and GenAI, can integrate these unstructured, multimodal inputs to generate predictive insights, making it possible to detect crop stress, simulate weather-driven scenarios, or localize advisory services.

2. Personalizing Services at Scale: Traditional extension systems struggle to deliver tailored guidance to millions of farmers. AI-powered tools, including natural language chatbots and predictive models, enable hyper-personalized advisories based on farm-specific conditions — in real time, at low marginal cost.

3. Enhancing Decision-Making under Uncertainty: AI models can simulate and forecast agricultural outcomes under diverse and uncertain conditions - such as disease outbreaks, drought, or shifting market trends. This allows both farmers and policymakers to make informed decisions in near-real time.

4. Augmenting Human Capacity through Automation: AI systems excel in tasks that require rapid, repetitive processing of visual or numeric data, such as disease diagnosis, quality grading, or soil health analysis. These systems extend the reach of human experts and improve efficiency in data-scarce environments.

5. Enabling ‘Invisible Infrastructure’: Many impactful applications, such as index-based crop insurance or market forecasting, depend on backend AI systems that work without direct farmer interaction. These “invisible” applications reduce transaction costs and make services accessible even in hard-to-reach communities.

While the potential of AI is vast, it is important to recognize where its use may not be strategic or cost-effective. Not every challenge in agriculture requires AI, and in many instances, simpler alternatives may offer more appropriate and affordable solutions. For example, in functions such as basic record-keeping, farmer registration, or the delivery of static market information, low-tech tools like SMS alerts, IVR systems, or printed materials may be more effective than complex AI platforms. In other cases, foundational issues such as weak infrastructure or dysfunctional institutions—like the absence of irrigation systems or under-resourced extension services—represent the real bottlenecks that AI alone cannot overcome. Moreover, the utility of AI diminishes significantly in data-scarce environments, especially where there is little high-quality information on local crops, soils, or weather. In such contexts, heuristic

or rule-based tools may yield more practical results. Lastly, in communities with low digital literacy or skepticism towards automated systems, AI-generated recommendations may lack trust or be poorly understood. Embedding AI within human support systems—such as trusted extension agents—remains critical to ensure adoption, usability, and impact.

While the high-leverage applications demonstrate AI's transformative potential, it is also important to recognize that not all impactful AI requires massive computational resources or cutting-edge infrastructure. Small AI—affordable, context-specific models that run on everyday smartphones or basic devices—is already delivering tangible results in resource-constrained environments. These lightweight solutions flourish on smaller datasets, operate with minimal connectivity requirements, and can be fine-tuned to address hyper-local challenges, making them particularly well-suited for smallholder agriculture in LMICs where infrastructure gaps remain significant.

AI applications in agriculture span the entire value chain, and numerous success stories have already demonstrated tangible impacts. Advanced AI-powered drones equipped with imaging sensors effectively detect early signs of plant diseases, nutrient deficiencies, and pest infestations, thereby enabling timely intervention and minimizing crop losses while reducing chemical usage by up to 95 percent.¹⁰

- IBM's Weather Company leverages AI-powered hyperlocal forecasting through its Weather Data API, analyzing satellite imagery, radar, and sensor data to help farmers optimize decisions about planting, irrigation, and harvesting.¹¹
- India's Saagu Baagu initiative has transformed chili farming in the Khammam district through an AI-enabled advisory service, doubling farmers' income to US\$800 per acre per crop cycle, increasing yields by 21 percent, reducing pesticide use by 9 percent and fertilizers by 5 percent, while improving quality to boost unit prices by 8 percent.¹²
- In Cameroon, Agrix Tech's AI-powered disease detection platform offers multilingual support including local African languages and eco-friendly treatment recommendations with 99 percent accurate disease identification, even without internet connectivity.¹³
- Kenya's M-Shwari¹⁴ provides digital savings and microloans to previously unbanked populations, particularly benefiting sugarcane farmers in regions like the Muhoroni subcounty.
- In Kenya and Nigeria, Hello Tractor uses AI and IoT data to provide predictive analytics and connect smallholder farmers with mechanization services; more than 9,000 farmers across both countries have been reached to date.¹⁵
- International research organizations are also leveraging AI; the International Rice Research Institute (IRRI) used machine learning and computer vision to dramatically improve rice seed characterization efficiency at the International Rice Genebank in September 2023.¹⁶

10 Meher, Kavitha, and Namitha (2024), <https://ijrpr.com/uploads/V5ISSUE5/IJRPR27031.pdf>

11 Wolfson (2019), <https://worldagritechusa.com/wp-content/uploads/2019/03/Dan-Wolfson-IBM.pdf>

12 WEF (2023), https://www3.weforum.org/docs/WEF_Scaling_Agritech_at_the_Last_Mile_2023.pdf

13 Business in Cameroon (2019), <https://www.businessincameroon.com/agriculture/0107-9276-cameroon-plant-disease-detection-app-agrix-tech-awarded-2019-special-presidential-prize-for-digital-innovation>

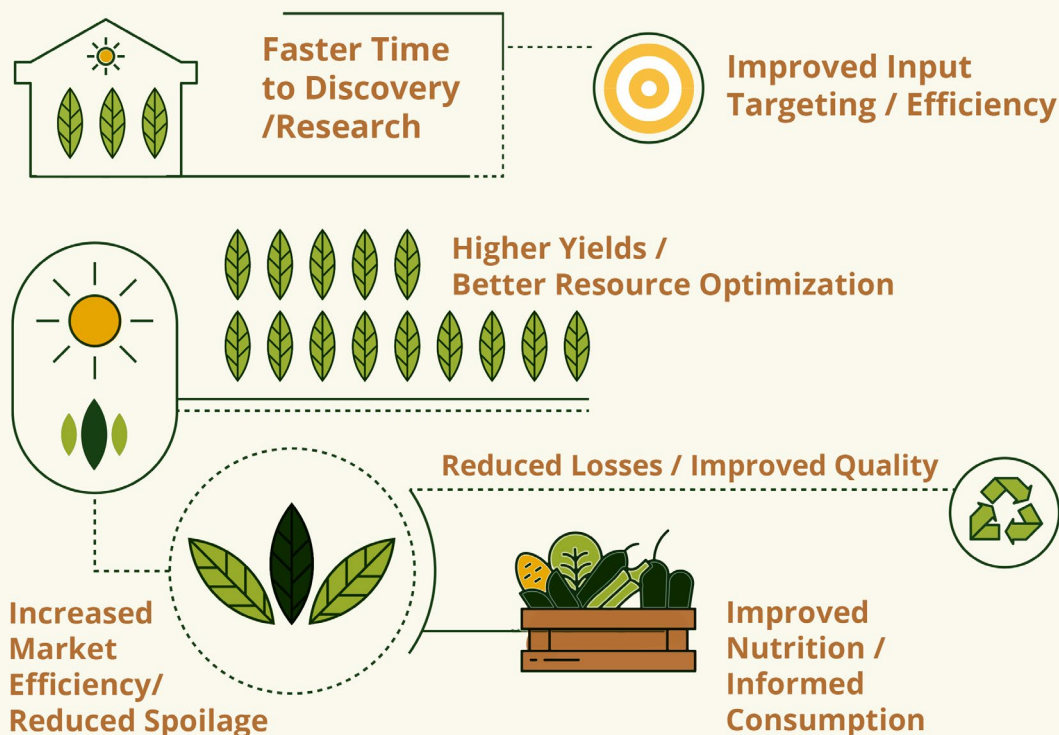
14 Fintech Association of Kenya (2024), <https://www.linkedin.com/pulse/five-ways-ai-changing-lending-kenyan-businesses-hgr8f/>

15 Atlas AI (2024), <https://www.atlasai.co/insights/powering-the-the-mechanization-revolution-in-smallholder-agriculture-with-ai>

16 IRRI (2023), <https://www.irri.org/news-and-events/news/irri-leveraging-ai-secure-food-and-nutrition-security-current-and-future>

Figure 1.4. Why AI for Agrifood Systems?

Impact



Source: Authors

Although SSPs benefit significantly from AI technologies, the transformative potential of AI extends to various stakeholders across the agrifood ecosystem. For policymakers, AI offers powerful tools to develop and implement sustainable agrifood systems that meet environmental goals and address challenges, such as climate change, pest outbreaks, and declining biodiversity. AI-powered crop prediction tools help policy makers optimize resources, mitigate risks, and plan for market demands, ensuring a more resilient and efficient agricultural system. High-resolution mapping from systems like GAEZ v4¹⁷ delivers classifications that include agro-ecological zones, soil suitability assessments, and land cover information, assisting policy makers in identifying maximum potential crop yields and optimal crop types for specific areas. For agribusinesses, AI technologies streamline operations across the value chain through automated quality checks and intelligent supply chain management. ClimateAi's ClimateLens platform¹⁸ delivers 1 km-resolution forecasts ranging from one week to six months, helping agribusinesses manage climate variability and optimize operations through seasonal forecasts and scenario analysis. Research institutions are leveraging AI to accelerate scientific discovery and innovation. For example, The Mining

¹⁷ <https://gaez.fao.org/>

¹⁸ <https://climate.ai/solutions-products/climate-lens-overview/>



Useful Alleles for Climate Change Adaptation¹⁹ project, led by the International Maize and Wheat Improvement Center (CIMMYT), uses innovative breeding methods to identify and deploy climate-resilient traits more effectively.

AI presents unprecedented potential to reshape agriculture - but it's true power lies not in ubiquity, but in strategic deployment. As this chapter has shown, AI adds the most value when applied to tasks involving high-volume data synthesis, complex predictions, and mass personalization — especially where human capacity is limited and context-specific decision-making is critical. However, AI is not a silver bullet. Real transformation depends on aligning AI tools with local realities, institutional readiness, and public good objectives. For AI to catalyze equitable and resilient food systems, it must be embedded in broader development strategies, paired with strong governance, inclusive data ecosystems, and foundational digital infrastructure. The chapters that follow examine how to move from promise to practice: identifying key enablers, sector-specific applications, and investment pathways to responsibly harness AI for agricultural transformation - with small-scale producers at the center.

¹⁹ ClimateAi's ClimateLens platform



02

Foundational Domains for AI in Agriculture: Conditions, Challenges, and Opportunities

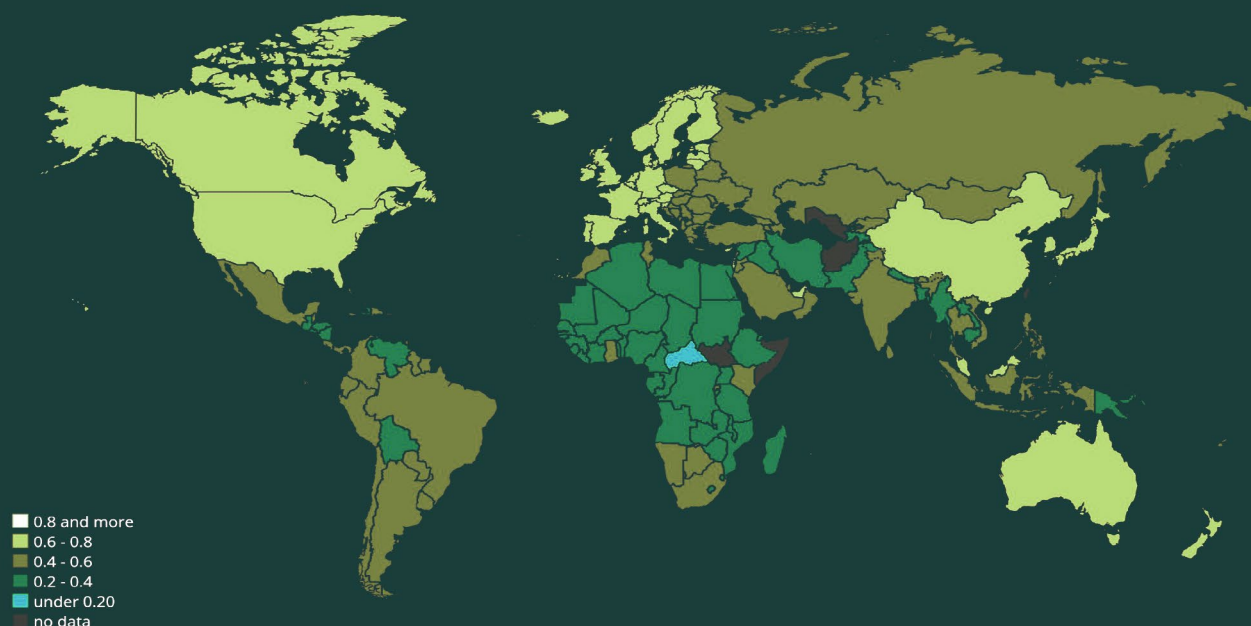
Realizing the transformative potential of AI in agriculture requires navigating a complex landscape of interconnected needs. Rather than treating enablers and barriers as separate categories, this chapter integrates both to provide a more grounded, actionable view of what it takes to deploy AI responsibly and at scale. The chapter is organized around five foundational domains, each essential for AI readiness, but all requiring different types of investment, coordination, and sequencing. For each domain, we explore its enabling role, current constraints, embedded challenges, emerging trends, and pathways forward.

Connectivity and Energy Infrastructure: The Physical Backbone

Why it Matters: One of the most pressing issues is the digital divide, as many regions, particularly in South Asia and Sub-Saharan Africa, lack the necessary infrastructure to support AI applications. The AI Preparedness Index (Figure 2.1) reveals significant disparities across countries in their readiness to leverage AI technologies. Nations in North America, Western Europe, and parts of East Asia demonstrate high levels of AI preparedness, with index values of 0.8 and above. In contrast, many countries in Africa, parts of South Asia, South America, and South-East Asia show lower preparedness levels, with index values below 0.4. This disparity underscores the need for targeted efforts to enhance AI readiness in LMICs, particularly in the agricultural sector where AI can have transformative impacts.



Figure 2.1. AI Preparedness Index 2023*



Source: IMF, AI Preparedness Index April 2024,
https://www.imf.org/external/datamapper/AI_PI@API/ADVEC/EME/LIC?year=2023

**The boundaries and names shown on this map do not imply official endorsement or acceptance*

What it Enables: Reliable internet access and consistent energy supply are non-negotiable for AI systems that rely on cloud computing, real-time data exchange, and edge processing. High bandwidth and low latency are particularly critical for applications like drone-based crop monitoring, autonomous machinery, and real-time pest detection.

Current Gaps and Barriers: Only 15% of rural Africa has internet access, compared to 50% in urban areas. Despite 83% mobile broadband coverage in Sub-Saharan Africa, only 25% use it due to affordability, digital literacy gaps, and poor device access. Stable electricity remains a core constraint, with over 600 million people in Sub-Saharan Africa lacking access. Latency and data routing inefficiencies also hinder near-real-time AI deployments.

Emerging Trends: The cost of connectivity and energy-efficient compute is declining. Small language models and on-device inferencing reduce the need for constant connectivity and high-power servers. In parallel, AI-generated user interfaces are beginning to dynamically adapt to user capabilities, lowering usability barriers.

Spotlight: BitCluster data center in Addis Ababa leverages renewable energy from the Grand Ethiopian Renaissance Dam, demonstrating how strategic partnerships with large-scale renewable energy projects can support digital infrastructure development.²⁰ This approach addresses power reliability issues and aligns with global sustainability objectives by reducing carbon emissions from digital operations.

²⁰ Business Wire (2025), <https://www.businesswire.com/news/home/20250220160575/en/Africa-Data-Center-Construction-Market-2025-2030-Modular-Data-Centers-are-on-the-Rise-Offering-Scalable-Energy-efficient-Solutions-for-Gradual-Expansion-As-Demand-Increases---ResearchAndMarkets.com>

Data Ecosystems: Fueling AI with Local Intelligence

Why it Matters: AI systems are only as good as the data that trains and informs them. In agriculture, most available data—on soil, crops, pests, or climate—originates in high-income regions and lacks local nuance. This creates blind spots and bias in AI outputs when deployed in LMIC contexts. Without inclusive data ecosystems, AI tools risk reinforcing inequalities, overlooking marginal crops, and excluding smallholder priorities. Building data systems that reflect diverse agroecological zones, practices, and farmer knowledge is a prerequisite for trustworthy and actionable AI in agriculture.

What it Enables: Granular, local data fuels the performance and equity of agricultural AI—from predicting climate risk to tailoring crop advice. Governance frameworks ensure responsible use, access, and consent.

Current Gaps and Barriers: Much of the data used in global AI systems excludes smallholders, indigenous practices, or region-specific crops. Data is often fragmented across agencies and formats. Lack of localized training data leads to model bias and limited relevance.

Emerging Trends: New retrieval-augmented generation (RAG) models offer ways to incorporate local knowledge without retraining large models. Open data commons and participatory data infrastructures are also being piloted to incentivize data contribution while upholding sovereignty.

Spotlight: In 2018, Ethiopia launched the “Coalition of the Willing” (CoW)²¹, a volunteer network of individuals and organizations focused on sharing soil and agronomic data to harness the potential of data-driven agriculture. The initiative has successfully facilitated the organization of tens of thousands of data points into a structured database, enabling machine-learning algorithms to perform detailed analysis. The CoW exemplifies how foundational infrastructure for data collection, storage, and sharing can transform agricultural practices in low and middle-income regions, making advanced AI applications possible in areas where they can have the greatest impact.

Human Capital and Digital Literacy: Equipping the Frontline

Why It Matters: Even the most advanced AI systems will fail if users don’t understand or trust them. In agriculture, this includes farmers, extension workers, local agribusinesses, and policymakers. With many LMICs facing digital literacy gaps - especially for women, older farmers, and those in remote areas - the risk of exclusion is high. Human capital is also a supply-side concern: very few professionals globally are trained at the intersection of AI, data science, and agriculture. Closing this gap is essential for designing, deploying, and scaling meaningful AI tools in the field.

²¹ <https://alliancebioversityciat.org/publications-data/coalition-willing-soil-and-agronomy-data-access-management-and-sharing>

What It Enables: AI's usefulness depends on whether people can understand and act on its outputs. Skills are needed at all levels—from digital literacy for farmers to AI fluency among agricultural researchers.

Current Gaps and Barriers: Training capacity is limited. Gender gaps, language barriers, and weak extension systems slow adoption. Many users lack trust in AI-generated advice, especially if it's not localized or understandable.

Emerging Trends: GenAI tools are now being adapted to local languages, and multimodal interfaces (voice, image, chat) are bridging literacy divides. Train-the-trainer models and youth-led digital fellowships are expanding reach.

Spotlights: Namo Drone Didi²² : Women-Led Agri-Tech Adoption represents a pioneering approach to addressing both human capital development and agricultural modernization challenges in LMICs. Launched by the Indian government, this initiative aims to equip 15,000 women-led Self-Help Groups (SHGs) with agricultural drones from 2024 to 2026, providing them with specialized technical skills while improving agricultural productivity. The program provides substantial financial support, including 80 percent subsidy on drone purchases (up to ₹8 lakh or approximately US\$9,600) and low-interest loans at 3 percent for the remaining costs. This carefully designed financial structure makes advanced technology accessible to rural women who would otherwise lack the capital to enter this field.



²² <https://www.pib.gov.in/PressNoteDetails.aspx?NotelId=153383&ModuleId=3>

Governance and Policy: Building a Framework for Trust and Scale

Why it Matters: Agricultural data is increasingly valuable and sensitive - linked to land ownership, production cycles, and individual livelihoods. Without clear legal frameworks and public trust, AI applications risk violating privacy, misusing data, or amplifying power asymmetries. Many LMICs still lack agricultural data governance policies or national AI strategies. The absence of farmer-centric safeguards makes adoption riskier and discourages public-private cooperation. Governance structures must evolve alongside technology to protect rights and incentivize innovation responsibly. Beyond the concerns about privacy, data misuse, and power imbalances, there are real-world cases where the lack of clear governance has led to problems. For instance, in the context of AI-driven precision farming, unauthorized access to data can result in severe consequences such as remote sabotage of crop management systems or manipulation of livestock environments. Additionally, biases in AI models - stemming from unrepresentative training data - can disadvantage smallholder farmers, leading to recommendations that are economically harmful or inappropriate for their specific contexts. This is particularly acute in LMICs, where regulatory frameworks are often underdeveloped, and farmers may have little control over their own data.

What it Enables: Clear governance builds public trust, prevents misuse, and aligns incentives. It encompasses legal rights, ethical AI standards, accountability mechanisms, and public procurement norms. Clear governance frameworks not only protect farmers but also enable more robust public-private partnerships and innovation.

Current Gaps and Barriers: Many countries still lack comprehensive data ownership definitions for farmers. Privacy regulations are in their infancy, and few jurisdictions have mechanisms to audit or regulate AI systems in agriculture. Trust is further undermined when data is collected and used without tangible benefits for farmers - such as improved yields, market access, or fair compensation. The Telangana Agricultural Data Management Framework (ADMF)²³ in India is an emerging example of a government-led effort to establish clear rules for data collection, sharing, and management, aiming to protect individual rights while advancing the sector.

Emerging Trends: Globally, there is a growing interest in participatory governance models, where farmers and other stakeholders are involved in shaping data policies. Sandboxing - allowing safe, controlled experimentation with data and technology - is also gaining traction to balance innovation with risk management. There is also increasing emphasis on algorithmic impact assessments and transparency benchmarks to ensure AI systems are fair, accountable, and beneficial for all stakeholders.

Spotlight: The Agricultural Data Exchange (ADeX) in India²⁴ provides a secure, standardized environment for data experimentation, fostering collaboration among farmers, developers,

²³ <https://it.telangana.gov.in/wp-content/uploads/2023/08/Agriculture-Data-Management-Framework.pdf>

²⁴ <https://adex.org.in/accelerating-agricultural-innovation-with-the-adex-sandbox>

and researchers while mitigating risks associated with data sharing. Developed through a partnership between the Government of Telangana, the World Economic Forum, and the Indian Institute of Science, ADeX acts as a DPI, facilitating real-time data exchange without storing the data itself. Its impact is significant: ADeX empowers the creation of innovative, data-driven solutions for farmers, accelerates agricultural research, and supports sustainable and efficient farming by making diverse datasets—such as soil tests, weather information, and crop trends - readily accessible.

Public-Private Ecosystems: Scaling Sustainably

Why It Matters: No single actor can deliver AI in agriculture at scale. Governments, startups, cooperatives, and donors all play distinct roles - but coordination is difficult without shared infrastructure. Digital Public Infrastructure (DPI) systems create the rails for interoperability: identity, registries, data sharing, and service delivery. In agriculture, these systems are underdeveloped. Yet without them, AI tools remain isolated pilots or vendor-locked platforms. A resilient public-private ecosystem enables inclusive innovation, reduces costs, and avoids fragmentation across actors and geographies.

What It Enables: Shared infrastructure—digital identity, registries, APIs—enables actors to plug into common systems, reducing duplication. PPPs also bring investment and innovation into public delivery systems.

Current Gaps and Barriers: Low interoperability, vendor lock-in, and fragmented pilots limit impact. Few DPI systems include agricultural data and services. Trust in PPPs can be low if perceived as extractive.

Emerging Trends: Open protocol models (like Beckn), shared service layers, and interoperable registries are gaining traction. Cloud costs for model training and hosting are falling, improving affordability.

The Agriculture Information Exchange Platform (AIEP)²⁵

The Agriculture Information Exchange Platform (AIEP) is an initiative funded by the Gates Foundation and implemented by GIZ in collaboration with various partners. The platform is designed to empower smallholder farmers in Kenya and Bihar, India, by delivering real-time, relevant, and contextual agricultural advice in natural conversations using local languages.

AIEP leverages Generative AI to tackle persistent challenges in public extension systems, such as limited access to high-quality advisory services, exclusion of women and marginalized groups or inefficiencies in scaling localized extension.

An open call for innovation attracted over 130 applications, from which 30 proposals were shortlisted. Selected applicants participated in ideation workshops in Kenya and India to refine their concepts and share learnings.

Ultimately, four innovation cohorts were selected and received grants to develop AI-driven agricultural advisory solutions for LMICs. A fifth cohort, Mshauri, was onboarded later. Together, these cohorts collaborate closely — sharing progress, addressing common challenges, and co-developing inclusive digital solutions.

The five Minimum Viable Products developed are now being tested with over 40,000 end users. Each solution emphasizes inclusivity, trust-building, and an omnichannel approach to maximize impact and accessibility:

- **DynAG (International Rice Research Institute (IRRI), CIMMYT, Gramhal, H3I, IFFCO Kisan, Dexian and Sumarth):** The dynAg platform is designed from the ground up and is available via the ai.sakhi app and IVR. Users can receive advisory on different value chains such as mushrooms, paddy, onions, as well as kitchen garden in the local languages Hindi, Magahi, Bhojpuri and Maithili.
- **Farmer.Chat (Digital Green, Karya, Gooney.ai):** Farmer.Chat is an AI-powered agricultural assistant developed for smallholder farmers in rural, low-literacy, resource-constrained environments. It supports seven languages (Swahili, Amharic, Hausa, Hindi, Odiya, Telugu, English) via text, voice, and image and offers personalized advice across 40+ crops based on local practices and needs.
- **Omnichannel Digital Assistant (Viamo, Producers Direct, HarvestPlus, Sahaj):** This IVR-based advisory solution for beans and wheat farmers in Bihar and Kenya supports English, Hindi, and Swahili, ensuring accessibility across diverse regions.
- **Tech for Her (Dalberg and DeHaat):** The solution from DeHaat and Dalberg is an open-source architecture enabling customized, inclusive and interactive information

²⁵ Digital Global (2025), <https://www.bmz-digital.global/en/agriculture-information-exchange-platform/>

exchange by last mile women farmers & extension agents, interoperable with omni-channels interfaces.

- **Mshauri (Opportunity International, DigiFarm, Gooey.ai):** Mshauri is a WhatsApp Chatbot integrated with an AI workflow platform by Gooey.ai. It's an iterated solution initially custom built as a Retrieval Augmentation Generation (RAG)-based application and has been first tested in Malawi.

Key Lessons Learned

- **Scaling Requires Partnerships:** AI solutions scale well but require multidisciplinary collaboration for effective, context-sensitive implementation.
- **High User Satisfaction:** In a June 2025 survey (by 60 Decibels), 800+ users rated the MVPs with a Net Promoter Score (NPS) of 60, well above digital agriculture benchmarks.
- **Natural Language AI is Promising but Complex:** NLP can significantly improve extension services, but it must be deployed with local validation, human oversight, and consideration of local contexts and challenges.
- **Agricultural Data Gaps:** Very few efforts focus on the peculiarities of agricultural data and smallholder systems to prepare AI-ready data that can help fine tune foundational models for domain-specific use.
- **Need for Open Data & Content:** Progress is hindered by a lack of openly available, high-quality agricultural datasets and content repositories.
- **Digital Public Infrastructure (DPI):** Integrating DPGs (Digital Public Goods) into DPI initiatives is promising but still early stage. Alignment on standards and protocols is essential for interoperability and reusability.

In the AIEP initiative, the cohorts deliver increments of the platform in monthly sprints. Common challenges are addressed collectively in dedicated workstreams like Monitoring & Evaluation, system architecture design or the utilization of language AI. This open exchange paired with regular end user engagement fosters innovation and ensures that the resulting advisory tools are meaningful and accessible to all.

03

Applications of AI in Agriculture

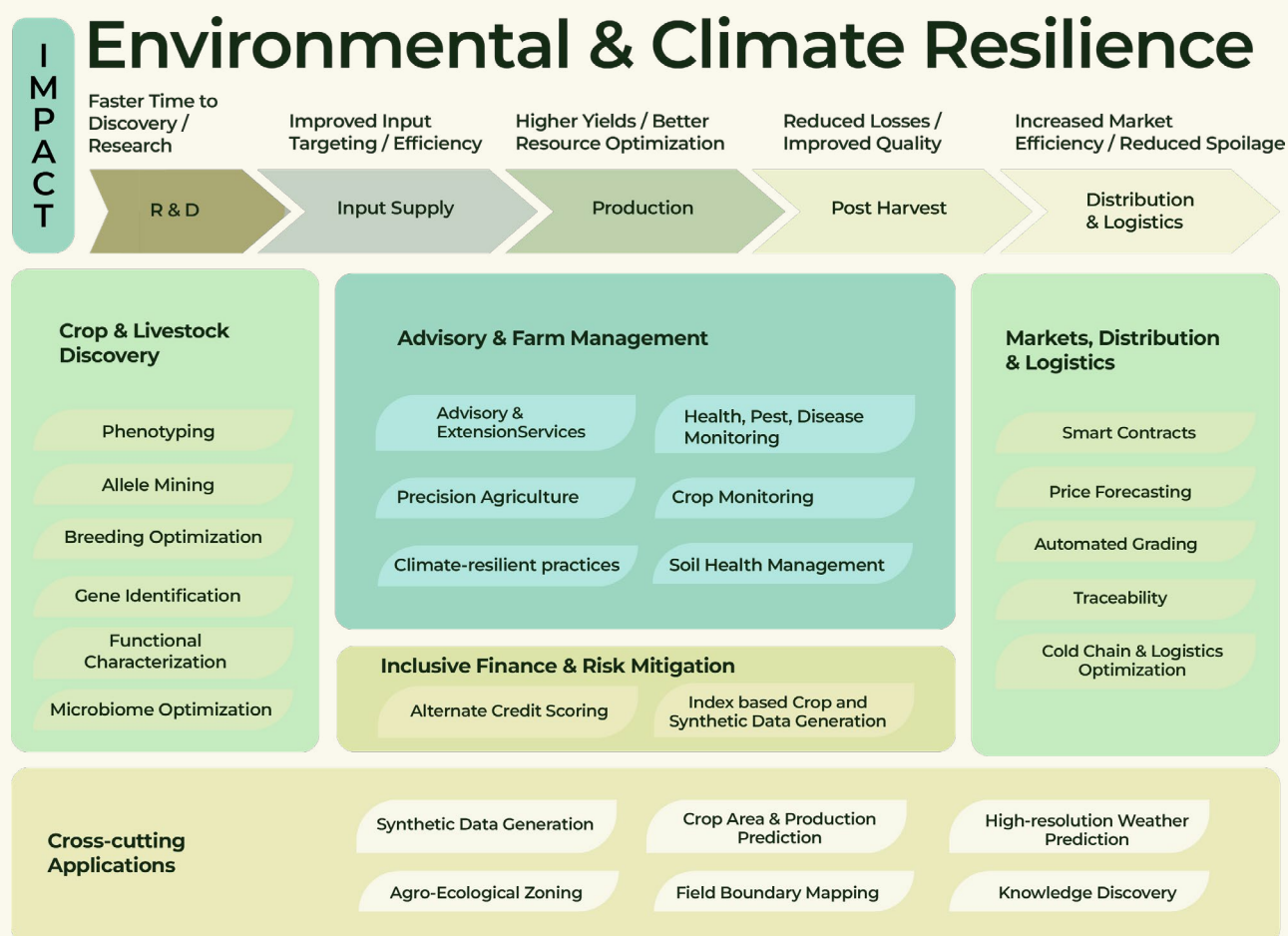
This chapter presents a systematic analysis of **AI applications in agriculture**, organized by their functional domains, and potential impact on agricultural systems. The use cases are presented across five key functional domains:



- **Crop and livestock discovery**
- **Advisory and Farm management**
- **Inclusive finance and risk mitigation**
- **Markets, distribution and logistics**
- **Cross-Cutting Applications**

The following sections provide detailed examinations of each functional domain, highlighting representative use cases that illustrate the transformative potential of AI across the agricultural value chain. Each section includes focused case studies that demonstrate practical implementations, key challenges, and emerging best practices in the application of AI to agricultural challenges (figure 4.1).

Figure 3.1. Selected High Impact Applications of AI in the AgriFood Sector



Source: Gates Foundation (2025)

Crop and Livestock Discovery

AI is revolutionizing the foundational aspects of agricultural research and development through enhanced capabilities in crop and livestock discovery. This domain encompasses critical research activities that underpin agricultural innovation, including phenotyping, allele mining, breeding techniques, bio inputs development, gene identification, and microbiome optimization. The application of AI in these areas is accelerating the development of improved crop varieties and livestock breeds with enhanced traits for productivity, resilience, and sustainability.

Phenotyping: From Manual to Automated Analysis - Traditional phenotyping, the assessment of an organism's observable characteristics, has historically been labor-intensive and subjective, limiting both the scale and precision of agricultural research. AI-powered image analysis has transformed this domain by enabling automated, high-throughput phenotyping systems capable of measuring thousands of plant and animal specimens with unprecedented accuracy. Deep learning algorithms, particularly convolutional neural networks (CNNs), now analyze images from various sources (satellites, drones, ground-based cameras, and microscopes) to quantify traits such as plant height, leaf area, disease symptoms, growth rates, and morphological characteristics. These systems extract meaningful patterns from complex visual data at speeds and scales impossible for human researchers, enabling the rapid identification of desirable traits for breeding programs.

Allele Mining and Breeding Optimization: Accelerated Trait Discovery - The genetic diversity preserved in crop and livestock gene banks represents an invaluable resource for addressing agricultural challenges. However, identifying beneficial genetic variants (alleles) from thousands of accessions has traditionally been a bottleneck in utilizing these collections effectively. AI approaches are now accelerating this process through the following:

- **Prediction of phenotypic traits from genomic data:** Machine learning models trained on existing phenotype-genotype datasets can predict the performance of uncharacterized genetic material, allowing researchers to prioritize promising candidates for field testing.
- **Optimization of breeding strategies:** Advanced algorithms model complex genetic interactions and environmental variables to design breeding programs that maximize genetic gain while maintaining diversity.
- **Simulation of evolutionary scenarios:** AI systems model how different selection pressures might influence trait development over generations, informing long-term breeding strategies.

Gene Identification and Functional Characterization: Mapping Genes with AI - Understanding the genetic basis of important agricultural traits is essential for both

conventional breeding and genetic engineering approaches. AI systems now help identify genes and genetic networks associated with desirable characteristics through the following:

- **Pattern recognition in genomic data:** Deep learning algorithms identify subtle patterns in DNA sequences that correlate with specific traits, even when the relationships are complex or nonlinear.
- **Protein structure prediction:** AI tools like AlphaFold are revolutionizing the understanding of protein structures, enhancing the ability to engineer enzymes and other proteins for agricultural applications.
- **Gene expression analysis:** Machine learning techniques reveal how genes are regulated under different environmental conditions, identifying key control points for important traits.

These capabilities significantly accelerate the process of understanding gene function, reducing the time and resources required to develop improved crop varieties and livestock breeds.

Microbiome Optimization: Invisible Allies - The microbiomes of soil, plants, and animal digestive systems play critical roles in agricultural productivity and sustainability. AI approaches are now helping researchers understand and optimize these complex microbial communities through the following:

Community analysis: Machine learning algorithms identify patterns in microbiome composition associated with plant and animal health, productivity, and resilience.

Functional prediction: AI models predict the metabolic capabilities of microbial communities based on their composition to inform strategies to enhance beneficial functions.

Interaction modeling: Network analysis algorithms reveal interactions between microbes and their hosts, identifying key species that mediate important ecosystem services.

These approaches enable the development of tailored microbial consortia for specific agricultural applications, from enhancing nutrient uptake in plants to improving feed conversion efficiency in livestock.

The International Rice Research Institute (IRRI), supported by Google.org's AI for Social Good program, is pioneering an AI-driven revolution in genebank utilization to combat climate change and ensure food security. Traditionally, only 5% of IRRI's 132,000 rice samples were used due to the slow and expensive nature of conventional screening methods. To address this, IRRI developed a machine learning system that analyzes seed images to identify, classify, and group germplasm with key traits like drought and flood tolerance. This innovation has already screened 60,000 accessions in one season—three times more than what was achieved in the past five decades for flood tolerance. The AI-based approach promises to complete full collection screening in just two years at one-sixth the cost, with projected economic returns of US\$30.79 billion over five years. Designed for scalability, the system has the potential to transform crop breeding globally, significantly boosting the utilization of plant genetic resources and advancing the UN Sustainable Development Goals.

The integration of AI into crop and livestock discovery is not merely enhancing existing approaches but fundamentally transforming how agricultural research is conducted. By enabling researchers to analyze vast datasets, identify complex patterns, and make predictions across multiple scales - from molecular interactions to ecosystem processes - AI is accelerating the pace of discovery and expanding the scope of what is possible in agricultural innovation. Table 4.1 summarizes key emerging trends in this domain, associated challenges, and future horizons as the sector moves toward AI-augmented agrifood systems that are both smart and inclusive.



Table 3.1 Trends, Challenges and Horizons - Crop and Livestock Discovery with AI

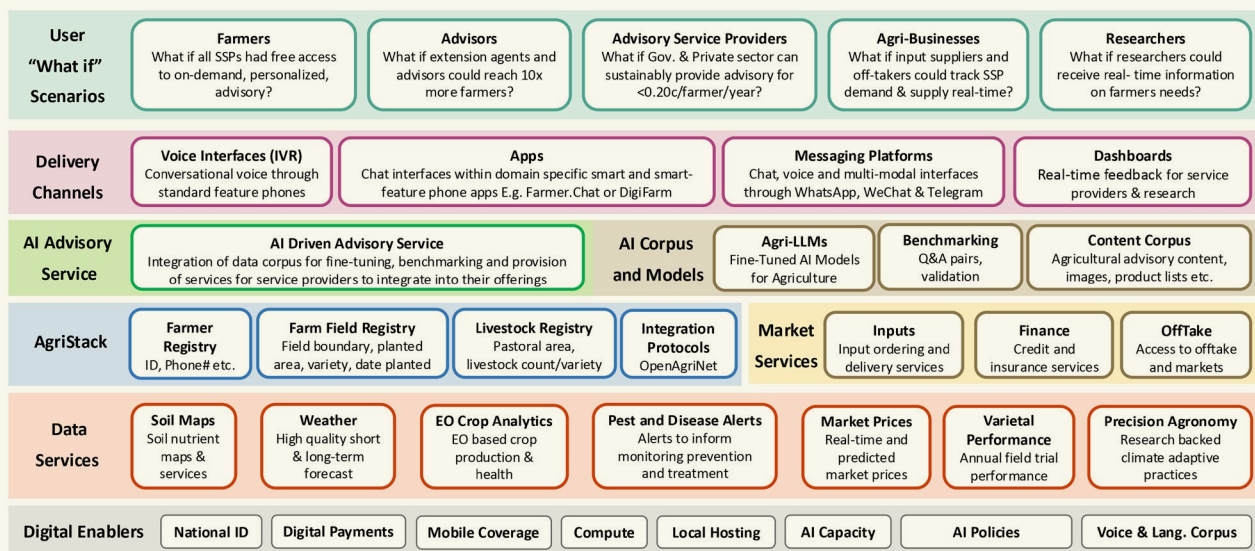
Key Emerging Trends	Challenges	Future Horizons
AI-powered phenotyping using deep learning and computer vision for trait analysis in crops and livestock. For example, drones, handheld imaging, and spectral tools.	High cost and technical complexity of imaging systems; limited annotated datasets for smallholder-relevant traits.	Affordable, open-access phenotyping kits and community-labeled datasets for crops in LMICs.
Genomic prediction and allele mining via machine learning to accelerate climate-resilient breeding.	Data silos across gene banks; lack of interoperable standards; underrepresentation of local varieties in training data.	Global digital breeding platforms using federated learning across multiple partners.
AI for modeling genotype with environment interactions to support breeding under climate stress.	Limited agroecological datasets; under-calibrated models in LMICs.	Climate-smart breeding models simulating trait performance across future climate scenarios.
Protein structure prediction (for example AlphaFold) for rapid gene function annotation and bioinputs R&D.	Expert interpretation required, limited adaptation to plant and microbial targets in agriculture.	Agriculture domain-specific protein prediction tools for crop trait improvement and enzyme design.
Microbiome engineering using AI to predict and design beneficial microbial consortia.	Context-specific efficacy of microbial blends; lack of scalable soil and gut microbiome data in the Global South.	AI-personalized biofertilizers and livestock probiotics tailored to soil types, climates, and crop-livestock systems.

Advisory and Farm Management

AI is transforming how farmers receive expert advice, how public institutions deliver agricultural services, and how farms are managed on a day-to-day basis. This domain encompasses digital advisory services (for example, AI-enhanced agricultural extension and farmer helplines), public sector service delivery (for example, government-led early warning systems and e-governance in agriculture), and farm management platforms that use AI-driven decision support to optimize on-farm decisions.²⁶ Agricultural extension services play a crucial role in supporting 570 million SSPs worldwide, contributing to food security and rural development through the dissemination of technical advice and best practices. These vital services, however, often face significant challenges, including weak institutional capacity, inadequate reach, and limited access to up-to-date scientific knowledge. Language is also a significant barrier. Advisories provided only in the world's predominant languages cannot easily be understood in many communities speaking regional or local languages and dialects.²⁷ A recent Nature Food study examined generative AI's potential to revolutionize agricultural extension services through LLM-powered chatbots.²⁸ The research identifies two transformative capabilities:

- LLMs can simplify complex scientific knowledge by finding, analyzing, and distilling technical information into accessible language for farmers and extension agents who lack time or specialized training to process lengthy scientific reports.
- LLMs can personalize agricultural advisories, moving beyond standardized recommendations to address the unique challenges faced by individual smallholder farmers through data-driven, tailored guidance based on specific situations.

Figure 3.2. An AI advisory stack requires integration of many components



Source: Gates Foundation (2025)

26 Farmer.Chat (2024), <https://arxiv.org/html/2409.08916v2#:~:text=Smallholder%20farmers%20are%20essential%20to,jama%20and%20Pizarro%2C%20%2056>

27 IFPRI (2025), <https://www.ifpri.org/blog/can-we-trust-ai-generate-agricultural-extension-advisories/#:~:text=Agricultural%20extension%20services%20play%20a,systemic%20challenges%2C%20such%20as%20videos>

28 Tzachor et al. (2023), https://www.nature.com/articles/s43016-023-00867-x.epdf?sharing_token=H0GuFj2W1qZjZ6-vMVntWNRgN0jA jWel9jnR3ZotV0NtXGsdSi40pRsG_6jTzulz_Y8PXDbHoH1H1eD_uw9cD24Qw5QLGR8G3mzf4nv6Zyo9aep_Z_CzqVf2Zw3v3E2XLoberomLR5V3-jji9q_bjWpD9A_jwxHeg-fern0qMGtjLMxrjuW8P-iPloueavPEph4Dd8JCB7RqbFr1RLV1UO5X54-46MG3tCmfpFRbCl%3D&tracking_referrer=www.ifpri.org

Generative AI is poised to overcome these persistent barriers. The evidence from early implementations is compelling:

- Digital Green's AI-powered chatbot²⁹ has grown rapidly to almost 400,000 farmers and extension workers in six countries and over a dozen languages. A recent evaluation shows that 70 percent of farmers take action based on FarmerChat recommendations
- iSDA's Virtual Agronomist, serving over 200,000 plots³⁰ in seven African countries, supporting 17 crops, and has boosted yields by up to 1.9-fold and profits by up to 4.7 times through AI-driven, personalized agronomic advice delivered via WhatsApp.
- In India, Kisan e-Mitra AI Chatbot³¹ has successfully resolved over 8.2 million queries from 5 million farmers regarding PM-KISAN (a direct benefit transfer program providing income support to smallholder farmers) in their own language.

Rather than replacing human agents, AI enhances them. Smartphone-based tools like PlantVillage Nuru³² let agents diagnose pests offline using computer vision. In Bihar, India, an extensionist used an AI assistant to confidently advise on climate-smart pest control, something previously requiring external consultation. AI enables "para-experts" by giving them up-to-date, localized guidance at their fingertips.

Public agencies are also using AI to predict and manage agricultural risks at regional scales. Machine learning models can analyze satellite imagery, weather trends, and pest incidence data to detect emerging threats and trigger timely alerts. The Kenya Agricultural Observatory Platform developed by KALRO with World Bank support exemplifies this approach; it combines real-time weather forecasts with remote sensing to deliver high-resolution agricultural advisories to 1.1 million farmers, helping them optimize planting and harvesting times.³³

Public sector use of AI is not limited to direct farmer advice; it extends to improving how governments allocate resources and design interventions. In Karnataka, India, an AI-based price forecasting tool analyzes market and production data to predict commodity prices three months in advance, informing the state's decisions on Minimum Support Prices and procurement planning.³⁴ This kind of predictive insight helps policy makers stabilize markets and prepare for gluts or shortages. Governments are also employing AI to monitor field conditions and target services. For instance, machine learning models processing satellite data can identify which districts are facing drought stress or pest infestation, thereby allowing authorities to channel extension efforts, input deliveries, or disaster relief to the most affected areas. During the COVID-19 pandemic, Togo's government used AI analysis of satellite imagery

29 <https://digitalgreen.org/a-new-frontier-for-farmer-chat-enhanced-smallholder-farmer-support-with-openais-operator-research-preview/>

30 <https://www.isda-africa.com/posts/virtual-agronomist-one-year/>

31 <https://www.pib.gov.in/PressReleasePage.aspx?PRID=2056695>

32 <https://openknowledge.fao.org/server/api/core/bitstreams/a67f6ac7-a1a9-44c2-ad89-a7ec79e510e3/content>

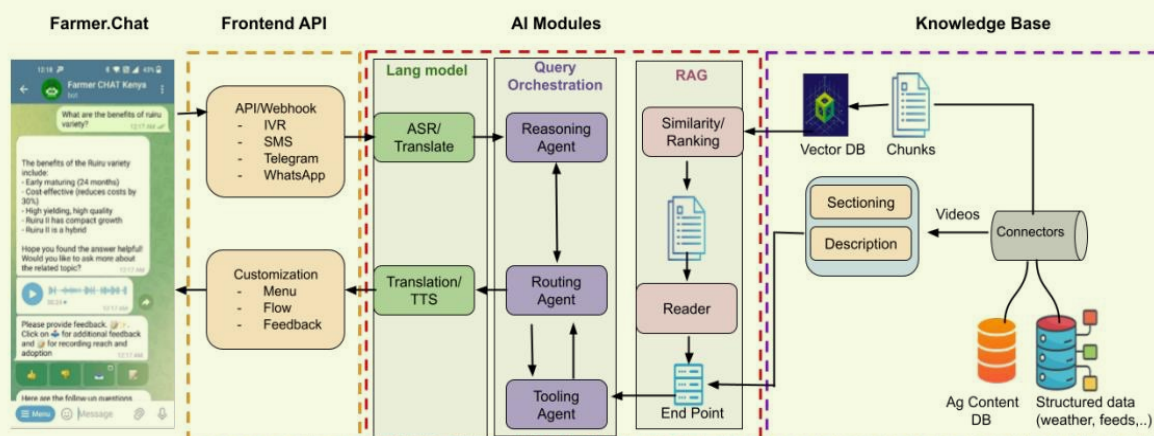
33 Jenane (2025), <https://blogs.worldbank.org/en/agfood/artificial-intelligence-in-the-future-of-sub-saharan-africa-far#:~:text=Another%20key%20initiative%20is%20the,mitigating%20risks%20from%20unpredictable%20weather>

34 Microsoft (2017), <https://news.microsoft.com/en-in/government-karnataka-inks-mou-microsoft-use-ai-digital-agriculture/>

and phone data to identify vulnerable populations and deliver cash assistance via mobile money,³⁵ illustrating how AI can enhance the precision of public aid delivery in agriculture. As digital data ecosystems mature, it is likely that ministries of agriculture will increasingly rely on AI-driven dashboards for everything from input supply chain management to tailoring agronomic advice for specific communities.

Farmer.CHAT

Farmer.Chat exemplifies how Generative AI can transform agricultural extension by providing personalized advice to smallholder farmers through accessible channels. Developed by Digital Green, this platform serves as open-source DPI to address critical gaps in traditional extension systems.



Architecture for Inclusive AI-Powered Agricultural Advisory

Farmer.Chat's architecture combines a comprehensive knowledge base with advanced AI modules to deliver contextually relevant agricultural information in resource-constrained environments:

- **Knowledge Base Builder:** Ingests diverse agricultural content from expert-vetted sources including research papers, policy documents, and multimedia resources, transforming unstructured data into structured, searchable information.
- **AI Modules:** Utilizes retrieval-augmented generation (RAG) to ensure factually accurate yet conversational responses, with specialized query orchestration that identifies user intent and accesses appropriate information sources.
- **Accessibility Features:** Supports multiple local languages with automatic detection and translation, offers voice input/output for low-literacy users, and

35 Blumenstock, et al. (2022), <https://cega.berkeley.edu/collection/ai-assisted-cash-transfers-togo/>

integrates with popular messaging platforms like WhatsApp and Telegram.

- **Continuous Learning:** Evolves through user feedback and conversation analysis, continuously improving response quality and knowledge coverage.

As an open-source digital public infrastructure, Farmer.Chat enables other organizations to build upon its foundation rather than starting from scratch. This approach helps them to:

- **Reduce** implementation costs and accelerates deployment in new regions
- **Facilitate** customization for specific crops, languages, and farming practices
- **Encourage** collaborative improvement through community contributions
- **Ensure** interoperability with other agricultural data systems

Early implementations show promising results in improving farmer decision-making and access to timely information.

Beyond advisory services, AI is increasingly embedded in farm management platforms that help farmers make better decisions and manage resources efficiently. These platforms serve as decision support systems (DSS), integrating data about weather, soil, crops, and markets to provide recommendations on day-to-day and seasonal farm operations. Modern farm management apps can track farm activities (planting dates, inputs used, expenditures); with AI, they can also analyze these data to generate insights - for example, alerting farmers if their fertilizer use is below optimal levels given the soil conditions or predicting yield based on crop growth observations. AI excels at recognizing patterns and forecasting outcomes, which is invaluable for farm planning. Using machine learning models (for example, random forests or neural networks), farm management systems can predict yields, pest infestations, or nutrient deficiencies before they happen. A case study in Brazil showed that AI models could forecast soybean yields for farmers up to 90 days before harvest with reasonably good accuracy, allowing better crop management and market planning.³⁶ On the farm level, having yield predictions enables better budgeting and storage planning. AI-driven micro-climate forecasting at the farm scale is also emerging; projects like DeepMC use deep learning to predict temperature and humidity in specific locations, helping farmers to time irrigation and spraying more precisely.³⁷ These predictive insights were once available only to large agribusinesses; now, through cloud-based services and smartphone apps, even smallholders in LMICs can access advanced forecasts that inform their decisions.

Perhaps the most immediate farm management gains from AI are in efficient resource use, particularly of water. Smart irrigation systems backed by AI are helping farmers apply

36 Monteiro, et al. (2022), https://www.researchgate.net/publication/363367413_Potential_Use_of_Data-Driven_Models_to_Estimate_and_Predict_Soybean_Yields_at_National_Scale_in_Brazil
37 Elbehri, et al. (2021), <https://doi.org/10.4060/cb7142en>

water judiciously. By analyzing inputs from soil moisture sensors, weather predictions, and crop models, an AI-based irrigation controller can decide exactly when and how much to irrigate each plot. Studies indicate that such AI-powered irrigation can reduce water usage by up to 50 percent while improving yields by approximately 30 percent, by avoiding over-watering and ensuring plants get the right moisture at critical growth stages.³⁸

Beyond irrigation, AI is increasingly being applied to optimize fertilizer use to help farmers strike the right balance between input costs and crop performance. One notable example is the Rice Crop Manager, a digital decision-support tool developed by the International Rice Research Institute (IRRI).³⁹ The application provides personalized fertilizer recommendations, including optimal types, quantities, and application timings, based on farmers' responses to a set of agronomic questions. To further improve both the accuracy and user experience, the team, led by IRRI scientist Shalini Gakhar, is integrating AI and machine learning to reduce the number of required inputs while drawing from additional data sources, such as satellite imagery, soil databases, and historical crop performance. These enhancements aim to make the tool faster, smarter, and more intuitive—particularly valuable in regions where digital literacy or time constraints limit engagement. Adapted in countries like Bangladesh, India and the Philippines, Rice Crop Manager reflects how AI is transforming fertilizer advisory from static templates to dynamic, data-driven recommendations tailored to each farmer's unique context.

Despite growth, adoption of AI-centric management faces barriers, especially in advisory delivery. Many smallholders are unfamiliar with software; tools must be simple and localized. Some platforms address this by creating dashboards for extension agents or cooperative leaders, who relay AI-generated advice to farmers—a model of human-AI collaboration. Sustainability of these systems is another concern. Many are funded by governments or NGOs and are free for farmers, but long-term financing is unclear. This presents an opportunity to explore new sustainability models, including private sector engagement or public-private partnerships (PPPs). These models could ensure continuity and scale while maintaining affordability for farmers.

To summarize, from personalized advisories to predictive farm management, AI tools are making agriculture more precise, inclusive, and adaptive. Early successes, higher yields, lower waste, and faster responses, demonstrate the promise of AI, especially when combined with human support and trusted delivery channels. As digital ecosystems mature and technology costs fall, even smallholders in low- and middle-income countries can benefit. Still, to unlock AI's full potential, the focus must remain on inclusivity, trust, usability, and long-term sustainability. With smart investments and cross-sector collaboration, AI can help build resilient, equitable food systems for the future.

38 Farmonaut (2025), <https://farmonaut.com/precision-farming/revolutionizing-agriculture-how-smart-irrigation-and-ai-are-transforming-water-management-for-sustainable-farming/#:~:text=%E2%80%9CAI,%E2%80%9D>

39 IRRI (2018), <https://www.irri.org/crop-manager>

Key Emerging Trends	Challenges	Future Horizons
Conversational AI for farm advisory: Chatbots and voice assistants delivering real-time, personalized guidance in local languages to any farmer with a phone.	Language and context limitations: Many AI models struggle with local dialects or lack region-specific agronomic knowledge, risking generic or inaccurate advice if not properly localized. Also, farmers may be hesitant to trust machine-generated recommendations initially.	Ubiquitous virtual advisors that fluently support any language or dialect, backed by regionally trained models. AI advisors will operate in a trust framework with certification (to ensure quality) and seamlessly hand off to human experts when needed – establishing a reliable ‘assistant for every farmer.
Predictive analytics in extension: Use of big data (weather, remote sensing, market trends) and machine learning to anticipate farm issues (pests, diseases, yield shortfalls) and provide early warnings or preventive advice.	Data gaps and quality: Reliable AI predictions require rich datasets (climate, soils, crop profiles) that are often sparse or nonexistent for remote and smallholder-dominated regions. Fragmented data ownership among agencies can impede integrated analytics.	Hyper-local forecasting systems feeding into extension: AI models trained on global and local data (via federated learning) will provide farm-specific forecasts. Governments will invest in open ag data repositories and community sensing will enhance accuracy.
Integrated farm management platforms: All-in-one apps that use AI to optimize resource use (water, fertilizer, labor) and scheduling on the farm, effectively creating a digital twin of farm operations.	Digital divide and adoption: Smallholders in LMICs may lack smartphones, connectivity, or skills to use advanced farm management apps. There is a risk that only better-resourced farmers benefit, widening equity gaps. Integrating diverse technologies into a user-friendly platform is technically complex and costly.	Inclusive smart farming ecosystems: Affordable, even offline-capable farm management tools (e.g., via SMS/USDD or low-cost devices) will bring AI guidance to resource-poor farmers. Public-private initiatives will subsidize hardware and provide training.
AI uptake in public extension systems: Mainstreaming of AI decision-support in extension agencies, for example, dashboards for extension managers that prioritize farmer queries, chatbots integrated into official advisory services, and AI-assisted content creation.	Institutional readiness: Limited technical capacity in agencies to procure, maintain, and update AI systems; risk of overreliance on AI without proper validation or understanding (the “black box” issue). Nascent policy and regulatory frameworks raise questions about accountability and ethical AI use in public services.	AI-augmented extension workforce: Extension agents will routinely use AI tools, supported by clear protocols and training. Digital innovation units will localize AI tools and enable AI-supported policymaking with strong governance.
Climate-smart decision support: AI systems guiding climate adaptation on farms, for example, recommender systems for climate-resilient crop varieties, automated stress alerts, and optimized cropping calendars aligned with shifting weather patterns.	Model robustness under change: As climate change accelerates, historical data may become less predictive of future conditions. Ensuring that models can update continuously and provide reliable advice is difficult. Resource-constrained farmers may struggle to act on AI recommendations without external support.	Adaptive and resilient AI systems: Future farm-management AI will include self-learning mechanisms that adjust to climate shifts. Paired with climate-informed credit and government support, AI will help farmers dynamically adapt plans and practices.

Inclusive Finance and Risk Mitigation

Inclusive finance and risk mitigation are critical domains where AI is democratizing access to financial services and enhancing resilience for agricultural communities. SSPs have historically been underserved by formal finance, due to high lending costs and lack of credit history or collateral. From machine learning-based credit scoring that evaluates farmers using non-traditional data, to AI-powered insurance that automates payouts for crop losses, AI-powered innovations are expanding financial inclusion for rural populations.⁴⁰ Importantly, many of these solutions target SSPs in Africa, Asia, and other emerging regions, reflecting a global push to make agri-finance more inclusive. Some applications are already mature and scaling (for example, mobile micro-loans with AI credit scoring), while others are emerging (for example, blockchain-enabled insurance); collectively, they promise a more financially resilient future for smallholders.

Alternative Credit Scoring: Financial Inclusion Reimagined

Traditional lending models often exclude smallholders, who typically lack formal credit history or collateral. AI has emerged as a transformative solution to this problem by developing sophisticated credit scoring models that go beyond conventional metrics. These systems analyze a wide range of alternative data—including farm size, crop health indicators, mobile phone records, purchasing history, satellite imagery, and even social and behavioral data—to assess farmers' creditworthiness. By tapping into such non-traditional data, AI-driven credit scoring can paint a more accurate risk profile of unbanked farmers, enabling lenders to extend credit where they previously could not. For example, M-Shwari in Kenya, launched in 2012 as a partnership between a bank and the M-PESA mobile money platform⁴¹, pioneered digital micro-loans for the unbanked. It uses telco mobile usage data in lieu of credit history to score customers, offering 30-day microloans via phone with instant, paperless approval. Within two years, it amassed over 10 million accounts (4.5 million active users) - roughly 20 percent of Kenya's adult population⁴²- demonstrating the scalability of AI-backed lending to small vendors and farmers. The service's low default rates and rapid uptake highlight how AI can lower costs and risks for lenders while broadening access for borrowers. Building on this model, Agri fintech startups are extending AI credit scoring specifically to farmers.

Apollo Agriculture in Kenya applies machine learning to an array of data (satellite imagery of fields, agronomic data, and mobile repayment behavior) to assess smallholder loan risk⁴³. It then provides input financing (for example, for seeds or fertilizer) and insurance bundled with advisory services, delivered via mobile apps and a network of field agents. This bundled service model, which aligns loan repayments with harvest cycles, has enabled thousands of Kenyan farmers to improve productivity with credit for quality inputs. Similarly, platforms like

40 RATIN (2023), https://ratin.net/site/news_article/13089

41 <https://www.safaricom.co.ke/media-center-landing/press-releases/cba-partners-with-safaricom-to-launch-m-shwari>

42 <https://www.cgap.org/blog/top-10-things-to-know-about-m-shwari>

43 <https://www.bii.co.uk/en/story/apollo-agriculture/>

Hello Tractor are using AI-driven analytics on tractor global positions system (GPS)/IoT data and farmers' records to create credit scores, helping mechanization service providers and smallholders to lease equipment on credit.

AI-based credit assessment is maturing - it has moved from pilot projects to real-world deployments that are reaching millions. Still, challenges remain. Algorithms trained on limited data may not fully capture on-the-ground risks, and there are concerns around data privacy and bias. Yet, the trajectory is clear—alternative credit scoring powered by AI is becoming a cornerstone of inclusive agri-finance, reducing loan approval times from months to minutes and unlocking capital for previously invisible farmers.

Index-Based Crop and Livestock Insurance: Automated Safety Nets

Small-scale farmers are highly vulnerable to weather extremes, pest outbreaks, and other shocks that can wipe out harvests. However, traditional crop insurance is often inaccessible to them, due to high transaction costs and the difficulty of verifying losses on many scattered small plots. AI-based systems can leverage machine learning and other techniques to analyze historical climate data, crop yields, and environmental trends to model risk, and they incorporate real-time remote sensing data (for example, satellite rainfall estimates or vegetation indexes) to trigger payouts automatically when predefined conditions are met. By relying on data-driven indices (such as “if rainfall in a region falls below x level, trigger a drought payout”), they eliminate the need for field loss assessments, drastically lowering overhead and making micro-insurance viable for small farms. Crucially, this protection reduces the downside risk of investing in better inputs. When farmers know they won't lose everything to a drought or flood, they can safely purchase improved seeds and fertilizer.

One pioneering example is the Agriculture and Climate Risk Enterprise (ACRE Africa) in East Africa. ACRE Africa has transformed smallholder resilience through mobile-enabled, weather-indexed insurance, protecting over 3.7 million farmers across Kenya, Rwanda, Tanzania, and Zambia against climate shocks since 2009⁴⁴. By integrating mobile platforms like M-PESA and USSD, the program reduced premium costs to near-SMS prices, enabling automated payouts during droughts or floods—such as compensating 80% of input costs during Kenya's 2009 drought. Another innovative player, Etherisc⁴⁵, combines AI with blockchain smart contracts to provide transparent, automated crop insurance in Kenya, India, and beyond. Its platform uses live weather feeds and satellite images to detect events like droughts or floods, then instantly executes payouts via smart contracts to farmers' digital wallets when triggers are hit. This approach increases trust (thanks to blockchain transparency) and speeds up compensation, which is crucial for farmers recovering from disasters. Meanwhile, Pula Advisors in Kenya has emerged as a leading Insurtech designing AI-driven insurance products for smallholders.

⁴⁴ <https://panagrimedia.com/acre-africa-cultivating-resilience-through-agricultural-insurance/>

⁴⁵ <https://www.cryptotrulism.org/blog/etherisc-using-blockchain-technology-to-deliver-crop-insurance>

Pula Advisors has revolutionized agricultural insurance for smallholder farmers by leveraging advanced data analytics, remote sensing, and digital platforms to deliver comprehensive, index-based coverage against drought, excessive rainfall, pests, and diseases across Africa, Asia, and Latin America⁴⁶. By embedding insurance into the cost of critical farm inputs like seeds and fertilizer - often making it free for farmers - Pula partners with governments, agribusinesses, and financial institutions to ensure broad accessibility and affordability⁴⁷. Their Area Yield Index and Hybrid Index products⁴⁸ use agro-ecological zoning and real-time data to trigger automated payouts, reducing administrative burdens and increasing trust among previously uninsured or unbanked populations. This approach not only protects millions of farmers from climate shocks but also enables them to recover quickly, reinvest in their farms, and improve food and financial security within their communities

Overall, AI-enabled index insurance is maturing from small pilots to large-scale programs: it is proving effective in managing covariate risks like drought and increasing farmers' resilience. Key challenges to address include basis risk (instances where an index might not perfectly reflect an individual farmer's loss), low awareness of insurance in rural communities, and the need for supportive regulation for these novel products. Going forward, however, the integration of AI, remote sensing, and fintech in insurance is expected to broaden the safety net for small producers, cushioning them against climate shocks and stabilizing livelihoods.

Several technical, social, and infrastructural hurdles continue to constrain the effective deployment of AI in agricultural finance. Despite these challenges, the trend is toward greater innovation and investment in this area. Global initiatives are emerging to funnel capital and expertise into AI for agricultural finance; for instance, recent partnerships⁴⁹ aim to insure 10 million farmers in Sub-Saharan Africa and South Asia by 2030 using advanced data tools. As digital ecosystems strengthen in rural areas, AI-driven finance and insurance for agriculture are expected to overcome current hurdles (table 4.4). The confluence of AI, big data, and fintech is opening new frontiers in inclusive Agri finance. One major opportunity is to develop hyper-local and personalized financial products, for example, credit and insurance tailored to individual farmers' risk profiles and cash flows, updated continuously with AI insights (for example, weather forecasts, market prices, and soil data). Another emerging horizon is the use of AI-powered advisories for financial decisions, such as chatbots that can guide farmers on optimal loan or insurance choices, or systems that dynamically adjust recommended insurance coverage levels from season to season based on evolving weather forecasts and risk predictions. Community-level AI solutions may develop - for example, cooperatives that use AI to aggregate members' data and negotiate better credit terms or group insurance. In terms of scale, what is experimental today (like blockchain-based insurance payouts) could become mainstream, leading to more transparent, efficient claim settlements across LMICs.

46 <https://www.unsgsa.org/stories/empowering-kenyan-smallholder-farmers-pulas-game-changing-digital-insurance>

47 <https://www.mercycorps.org/what-we-do/ventures/pula>

48 <https://www.pula-advisors.com/crop-insurance/>

49 <https://www.bayer.com/media/en-us/bayer-and-pula-foundation-partner-up-to-insure-10-million-smallholder-farmers-in-sub-saharan-africa-and-south-asia/>

Table 3.3. Innovations, Barriers, and the Road to Inclusive Financial Ecosystem with AI

Key Emerging Trends	Challenges	Future Horizons
AI-driven alternative credit scoring (using mobile usage, satellite imagery, and farm data to assess unbanked farmers' creditworthiness). For example, ML models evaluate crop health and phone payment history to extend loans to smallholders.	Data gaps and quality issues (sparse credit data on smallholders, noisy satellite inputs). Algorithmic bias (models may favor farmers with larger digital footprints). Regulatory hesitancy (financial regulators unsure about approving opaque	Wider adoption by banks and MFIs—alternative scoring becomes standard for agriloans, backed by regulators. Richer data integration—inclusion of IoT sensor data (such as soil moisture) to improve credit risk models. Federated learning networks where lenders pool data to create more robust, unbiased credit AI for smallholders.
Bundled digital financial services (integrated platforms offering loans plus insurance, advisory, and market linkages). For example, one-stop apps like Apollo provide input credit, crop insurance, and agronomic advice together.	Complex delivery models (requires coordination between banks, insurers, and agri-service providers). Farmer onboarding and literacy (multiple services can confuse users without proper guidance). Sustainability and business model (profitability can be challenging when offering subsidized bundles to the poorest farmers).	"Super-apps" for farmers—unified platforms (potentially backed by public-private partnerships) where farmers access credit, insurance, advice seamlessly. Personalized bundles—AI tailoring the mix of services (loan size, insurance level, advice type) to each farm's needs. Embedded finance in value chains—buyers and suppliers integrate AI-driven finance offers into contracts (for example, crop buyers providing pre-harvest loans and insurance in one package).
AI-powered index insurance (weather-index or satellite-index insurance products that auto-trigger payouts). For example, parametric drought insurance models using rainfall data and ML yield forecasts to compensate for losses.	Basis risk (payouts sometimes do not match individual losses, undermining trust). Low adoption (farmers unfamiliar with insurance; cultural and educational barriers to buying it). Actuarial data limitations (short historical climate records in some regions make AI risk models less reliable).	Hyper-local indices—AI combining satellite, drone, and ground sensor data to create farm-specific insurance triggers, reducing basis risk. Climate-adaptive insurance—products that adjust coverage dynamically based on seasonal forecasts (powered by AI climate models). Scale-up via government schemes—states integrate AI-index insurance into social protection or disaster relief programs for farmers.
Blockchain and smart contracts for agri-insurance (using decentralized tech for transparency and automation).	Technology access (rural farmers may not have connectivity or digital wallets to directly use blockchain solutions). Interoperability and standards (ensuring AI risk models reliably connect with various blockchain systems and data oracles). Regulatory uncertainty (many jurisdictions lack frameworks for blockchain insurance and may be slow to approve or recognize such policies).	Decentralized insurance consortia—farmer co-ops or local entities pool risk on blockchain, with AI advisors setting fair premiums, creating community-owned insurance funds. Instant claims and payouts becoming routine—smart contracts + AI damage assessment enable near real-time settlement, boosting farmer confidence in insurance. Global risk pools—interoperability allows smallholder index insurance to tap international reinsurance via blockchain, spreading risk and lowering premiums.

Markets, Distribution, and Logistics

Artificial intelligence is transforming how agricultural products move from farms to consumers, especially across LMICs. By enhancing efficiency, transparency, and coordination, AI is helping to streamline each stage of the agrifood supply chain. From crop harvest to final sale, both traditional AI (like machine learning and computer vision) and emerging generative AI tools are being applied to optimize logistics, improve market access, and reduce waste. Governments, international organizations, and agribusiness firms are increasingly partnering to deploy these technologies, ensuring that smallholder farmers and agri-entrepreneurs in LMICs can benefit from smarter distribution networks and market systems. Potential benefits range from better pricing data for farmers to lower food loss and improved food safety, as highlighted by FAO's Director-General.⁵⁰ In short, AI-driven innovations in this domain contribute to more efficient value chains, fairer markets, and greater inclusivity in global agrifood systems.

Quality Testing and Grading

Ensuring the quality and safety of agricultural produce is a critical market function—one that AI is rapidly transforming. Traditional manual inspections of crops, milk, or meat can be slow, subjective, and error prone. AI technologies, especially computer vision and sensor-based machine learning, now enable automated grading and contaminant detection with speed, consistency, and transparency. Advanced image recognition systems, for example, can sort fruits and vegetables by size, color, and defects at high throughput, reducing labor needs and minimizing disputes by providing objective, trusted quality metrics. Several companies are already applying this technology at scale. In India, Intello Labs uses smartphone cameras and cloud-based AI to assess produce quality by analyzing traits like color, texture, and damage—returning a trusted grade that supports fairer pricing along the supply chain.⁵¹ In Japan, Daiwa Computer Company has developed an AI-enabled melon grading system to automate inspections and ease labor demands.⁵² While early tests show promise, additional research and development are needed to bring the system into full operation.

In the livestock sector, AI is being used to examine products like meat and milk. In Australia, for example, an AI-powered video analysis tool, the MEQ Camera, that can grade beef marbling and color via a simple smartphone camera, analyzing muscle characteristics in real time.⁵³ This approach to using video for meat grading yields immediate and consistent results that processors can share instantly across the supply chain. It uses AI to give the solution stronger

50 FAO (2024), <https://www.fao.org/newsroom/detail/fao-highlights-the-potential-of-ai-and-the-digital-revolution-to-transform-the0-world-and-its-agrifood-systems/en#:~:text=He%20noted%20that%20E2%80%9DDigital%20agriculture,seeds%2C%20fertilizer%20and%20sustainable%20practices>

51 Intello Labs (2021), <https://www.intellolabs.com/>

52 <https://www.contec.com/case-studies/agriculture/daiwa-computer/>

53 Food Technology and Manufacturing (2023), <https://www.foodprocessing.com.au/content/ingredients/news/using-the-power-of-ai-in-meat-grading-538080921>



integrity as it grades from data-rich video instead of still images. Such technologies ensure that quality standards are met and help producers command premium prices for higher-grade products.

Another frontier is spoilage and contaminant detection. AI algorithms paired with novel sensors (such as “electronic noses” and spectral analyzers) can rapidly detect food safety hazards that once required lengthy lab tests. For instance, machine learning models have been trained to identify chemical adulterants in milk or grain by analyzing spectral signatures within seconds⁵⁴. DNA sequencing combined with AI has also been used to catch microbial contamination early in dairy processing. These AI-driven safety checks enable faster responses to unsafe food, thereby protecting consumers. Hydra platform by AgShift is an example of this technology in action. Using advanced computer vision and deep learning, Hydra automates quality grading for various food products, including strawberries, cashews, and seafood.⁵⁵ The system captures high-resolution images to assess quality markers like size, color, and defects within three minutes, providing a level of precision and consistency impossible through traditional methods. Hydra efficiency reduces food waste by minimizing handling and rejections and allows for higher sample sizes in quality checks. Additionally, its mobile-friendly interface enables quality assessments via smartphones, making it accessible for farmers and producers in remote areas. This

54 <https://www.nature.com/articles/s41598-022-25452-3>

55 AgShift Hydra—Power the Transformation of Food through AI, <https://www.agshift.com/>

scalable, connected ecosystem supports trend monitoring and operational efficiency across the supply chain, ultimately promoting better quality control and reduced waste.

Supply Chain Optimization and Market Intelligence

AI is increasingly the backbone of smart supply chains in agriculture, optimizing everything from route logistics to demand forecasting. Once agricultural goods are graded and aggregated, the next challenge is efficient distribution—getting products to the right market at the right time and at a fair price. A core application is using AI-based analytics to reduce the notorious post-harvest losses in food systems. Globally, 13.8 percent of food is lost post-harvest, costing around US\$1 trillion annually; losses for perishables like fruits and vegetables reach up to 50-70 percent.⁵⁶ By analyzing real-time data on production, market demand, and transportation, AI systems can dynamically route produce in ways that minimize spoilage. For example, AI routing algorithms can dispatch collection trucks in optimal sequences or suggest the nearest high-demand market for a farmer's crop. Predictive logistics platforms ingest factors like road conditions, weather, and order volumes to constantly refine delivery plans. In India, where up to 40 percent of some crops can be lost between farm and market due to handling delays and lack of storage, such AI-driven coordination is a game changer. Even small improvements - for example, better truck loading or direct farm-to-retail deliveries - have cut losses substantially in pilots. GenAI augments this by allowing “digital twin” simulations of supply scenarios: logistics planners can ask a GenAI model to simulate, for instance, how a flood might disrupt a distribution network, and get contingency plans.⁵⁷

AI is also enhancing market intelligence and price prediction for agricultural commodities. Farmers and traders have always faced volatile prices; sudden gluts or shortages can swing incomes drastically. Now, machine learning models (including deep learning and ensemble methods) are being trained on historical price data, weather patterns, crop forecasts, and even satellite imagery to forecast commodity prices weeks or months ahead. For instance, the startup Helios AI recently launched an app called ComodiTrack that uses global climate data and AI to predict price movements for 58 commodities, including corn, soy and wheat, and to offer buy/sell recommendations to farmers and procurement teams.⁵⁸ Such tools give stakeholders a heads-up on likely price rises or drops by correlating drought indicators or planting trends with market outcomes. “Hyper-local” price prediction models are also emerging; in China, researchers have combined seasonal climate forecasts with machine learning to accurately predict vegetable market prices in advance.⁵⁹ These forecasts help farmers decide when to sell or store produce and help governments anticipate and stabilize food prices. As a form of GenAI, LLMs can contribute by swiftly analyzing unstructured

⁵⁶ <https://panagrimedia.com/acre-africa-cultivating-resilience-through-agricultural-insurance/>

⁵⁷ <https://www.cryptotrism.org/blog/etherisc-using-blockchain-technology-to-deliver-crop-insurance>

⁵⁸ Walter (2025), <https://www.agriculture.com/new-ai-tool-uses-climate-data-to-predict-commodity-price-changes-8782079#:~:text=ComodiTrack%2C%20from%20Virginia,buy%20and%20sell%20recommendations%20accordingly>

⁵⁹ Guindani et al. (2024), <https://www.sciencedirect.com/science/article/pii/S2405844024165991>

data like news feeds, social media, and policy announcements that might affect commodity markets. For example, an LLM might parse a new export policy or a disease outbreak report and incorporate it into price forecasts to provide a richer context than numeric data alone.

Beyond predictions, AI enables better demand-supply balancing in near real time. Digital marketplaces now use AI matching algorithms to connect surplus on the farm with deficits in markets. These platforms analyze incoming buyer orders and available farm inventory, then automatically trigger procurement and distribution to fill gaps, thereby reducing oversupply in one region while alleviating shortages elsewhere.⁶⁰ Such systems were crucial during COVID-19 disruptions, for instance, where AI helped reroute agricultural produce that otherwise would have been dumped, instead finding buyers through e-commerce channels. On the supply side, AI-driven inventory management can monitor storage conditions such as temperature and humidity and predict the shelf life of perishable goods, so that products are sold in order of urgency. This granular management, often aided by IoT sensors and AI, prevents spoilage and ensures freshness for consumers.

Digital Traceability and Smart Contracts

As agriculture supply chains go digital, traceability—the ability to track a product’s journey from farm to fork—has become a top priority. Consumers, regulators, and farmers all benefit from transparent supply chains: they enable proof of origin (critical for organic or fair-trade products), rapid recall of contaminated foods, and assurance against fraud. AI and blockchain technologies are jointly powering next-generation traceability systems in the agrifood sector. Blockchains (distributed ledgers) provide an immutable record of each transaction or handoff in the supply chain, while AI ensures that the data recorded are accurate and actionable. Together, they tackle a costly problem: food fraud and opacity. Food fraud (such as dilution, mislabeling, or counterfeiting of food products) is estimated to cost the global food industry on the order of US\$10-15 billion every year.⁶¹

One application is provenance tracking for high-value or sensitive products. Coffee, cocoa, and organic produce are examples where buyers increasingly want to know the exact source. AI-based systems can use identifiers such as QR codes or digital tokens to tag each product batch; and record attributes like farm GPS location, quality grade, and certifications. Although the QR code itself is not AI, it acts as a digital anchor linked to richer datasets. AI plays a role in verifying, analyzing, and synthesizing these data - such as assessing quality through computer vision; or detecting anomalies in sourcing. When this information is logged to a blockchain, it becomes tamper-proof and easily shareable with end-consumers, enabling traceability and transparency across the value chain. IBM’s Food Trust platform is an example that has been used by retailers and food companies globally to trace products (from lettuce to pork) in

60 Brilliant Brand Strategies Spectrum Blog, <https://brilliantbrandstrategies.com/spectrum-blog/Revolutionizing-African-Logistics-How-AI-is-Bridging-the-Gap-in-Infrastructure-Challenges>

61 US FDA (2024), <https://www.fda.gov/food/compliance-enforcement-food/economically-motivated-adulteration-food-fraud>

seconds. Now, projects are extending such systems to smallholder farmers. In Honduras,⁶² a partnership between IBM and Heifer International is using IBM Food Trust (blockchain) plus AI analytics to integrate coffee and cocoa smallholders into transparent supply chains. Farmers in a cooperative there can record their crop data via a mobile app; the blockchain ledger then tracks each lot from farm to export, and AI from IBM's Watson platform helps analyze yields and quality to improve farmers' production and market outcomes. Increased transparency is expected to reduce the exploitative middlemen margins (which caused farmers to lose approximately 46-59 percent of value previously) and allow farmers to earn a premium by proving the quality and origin of their beans.

Compliance and certifications are also being streamlined. For organic produce or fair-trade goods, AI can cross-verify reported practices against data; for instance, satellite imagery and IoT soil sensors might feed an AI model to confirm that a farm truly abstained from prohibited chemicals, a requirement for organic certification. These verified data points can be written to blockchain records as a permanent certificate. Smart contracts (self-executing contracts on blockchain) can automatically enforce certain rules, for example, releasing a payment to a farmer only when a third-party lab's AI-tested food safety report is uploaded, or automatically rejecting a shipment that does not have a valid digital phytosanitary certificate. In international trade, such smart contracts reduce paperwork and delays. A shipment of grain, for example, can have its invoice, quality certificate, and customs documents all shared via a blockchain network to relevant parties, and an AI agent can instantly check them for completeness or discrepancies. Once all conditions are met, the smart contract might trigger the warehouse to release the goods and the bank to release payment—all without traditional emails or bank guarantees. This process greatly speeds up transactions and lowers transaction costs. AI further enhances traceability by monitoring data flows for anomalies. Machine learning models can be trained to detect suspicious patterns in supply chain data (for instance, a sudden jump in yield reported from a farm could indicate record falsification, or an unusual gap in temperature data in a cold chain could imply spoilage). By flagging such issues in real time, AI helps auditors focus on potential breaches in compliance or quality.

GenAI, particularly LLMs, can also make the deluge of traceability data more usable. For instance, consumers or buyers may not want to read through raw logs of every step their food took. An LLM interface can be layered on top of the traceability system: a user could scan a product QR code and ask in natural language, "Where did this mango come from, and was it organically grown?" The AI assistant would then generate a concise narrative: "This mango was grown by Farmer A in Region X, harvested on June 12, transported via ColdChainCo (maintaining 4°C), and certified organic by Authority Y verified on the blockchain." This makes traceability information accessible and trustable to broader stakeholders and not only data specialists.

62 Dotson (2021), <https://siliconangle.com/2021/07/07/heifer-ibm-use-blockchain-ai-assist-honduran-coffee-cocoa-farmers/>

Despite this promise, AI applications in markets, logistics, and traceability face several persistent challenges. Infrastructure gaps—especially in last-mile internet, device availability, and digital skills—limit AI adoption by smallholders and local traders. Data remain fragmented and often unstructured across the value chain, while concerns persist about data privacy, trust in AI recommendations, and interoperability between traceability systems. Moreover, without clear standards and inclusive governance frameworks, digital transparency tools risk excluding or penalizing smaller producers rather than empowering them.

Yet, emerging trends show strong momentum toward smarter, more inclusive agrifood systems. Automated quality testing is becoming faster and cheaper. AI-powered price and logistics forecasting is reducing waste and volatility. Blockchain and digital traceability tools are gaining adoption across high-value export crops and expanding into domestic supply chains. GenAI is now enabling natural-language insights and document automation, potentially opening advanced systems to non-experts. Together, these innovations are driving a shift to more transparent, efficient, and equitable value chains.

Table 3.4. Trends in Markets, Distribution and Logistics with AI

Key Trends	Challenges	Future Horizons
Automated Quality Testing: AI-powered grading for crops, milk, and meat is improving speed and consistency.	Limited access to AI tools and infrastructure among smallholders.	Widely deployed, low-cost grading devices in rural markets.
Predictive Logistics and Pricing: AI forecasts market demand and optimizes supply chains.	Fragmented data, lack of trust in AI outputs, and shocks to models.	Self-adjusting, resilient supply chains powered by AI.
End-to-End Traceability: AI and blockchain enable product tracking and verification from farm to fork.	Siloed systems, data privacy concerns, and inconsistent standards.	Interoperable, global traceability with smart contract trade.
GenAI for Market Insights: GenAI synthesizes news, policy, and signals for decision support.	Data quality, hallucination risks, and explainability gaps.	Natural language interfaces for agrimarket intelligence.

Cross-Cutting Applications

AI also offers a suite of cross-cutting applications in agriculture that underpin multiple stages of the agrifood value chain. These AI-driven solutions transcend individual subsectors, providing broad benefits from farm planning to market management.

Crop Area and Production Prediction

AI-powered crop area and yield prediction tools combine remote sensing, geospatial data, and machine learning to estimate what crops are grown and where and how much will be produced. By analyzing satellite and drone imagery alongside weather and historical data, these systems can monitor planting patterns and crop health in near real time. The resulting predictions of harvest area and output help governments and agribusinesses optimize resource allocation, plan market logistics, and activate early responses to potential shortfalls, thereby improving food system resilience. Crucially, AI enables these predictions to be faster and more granular than traditional methods—detecting changes in crop conditions as they happen and forecasting yields with increasing accuracy. This capability leads to more proactive decisions in deploying storage, transport, and price stabilization measures. Multiple operational platforms demonstrate the impact of AI in crop monitoring. For instance, national crop observatories now use machine learning to interpret satellite data for acreage estimates before harvest. Near real-time intelligence on crop development allows for early warning of drought or pest impacts on production. In LMICs, such AI-driven forecasting is helping to target food security interventions by providing objective, timely evidence of which regions may face deficits. By reducing the uncertainty around agricultural output, AI-based area and yield prediction supports better planning from the farm level (for example, deciding input use) up to national policy (for example, arranging grain imports or strategic reserves in anticipation of a poor season).

Sen2-Agri, developed by the European Space Agency (ESA), is a system that processes satellite imagery for agricultural monitoring through machine learning. This system leverages Sentinel-2 and Landsat 8 data, offering 5-day revisit cycles and free access to data.⁶³ It generates cloud-free composites, classifies cropland, maps crop types, and assesses vegetation health, enabling comprehensive agricultural monitoring from local to national scales.⁶⁴ Sen2-Agri applies machine learning algorithms to streamline the data processing pipeline. AI plays a central role by automating the production of crop-specific monitoring outputs and ensuring consistent quality through the integration of in situ data for calibration and validation. Similarly, CropWatch monitors global agricultural conditions using satellite data to assess crop health and food production, offering essential insights for governments, policy makers, and international organizations.⁶⁵ The system tracks temperature, rainfall, solar radiation, and

⁶³ ESA Data User Element, https://due.esrin.esa.int/page_project159.php. Accessed November 8, 2024.

⁶⁴ Defourny et al. (2019), <https://hdl.handle.net/10568/107771>

⁶⁵ CropWatch Bulletin (2023), <http://cloud.cropwatch.com.cn/web/report/detail?id=288>

biomass indicators while using unsupervised classification and agro-meteorological models to estimate crop acreage and yields. These data helps stakeholders manage food security through early warning of potential risks.

Agro-Ecological Zone Mapping and Environmental Characterization

Understanding the suitability and condition of land is foundational to sustainable agricultural development, climate adaptation, and ecosystem restoration. AI is transforming how we assess land by enabling high-resolution, dynamic mapping of agro-ecological zones (AEZ) and by advancing environmental characterization—such as measuring soil health, monitoring degradation, and estimating carbon content. These capabilities are critical in a world where land degradation, climate variability, and unsustainable farming practices threaten both productivity and resilience. This section explores how AI-driven tools are accelerating insights into land potential and condition through two key lenses: land use planning and land restoration monitoring (box 4.14).

AEZ mapping is a comprehensive approach to land-use planning that evaluates an area's potential for crop production.⁶⁶ Identifying the right crops for the right land is critical for sustainable agriculture. By cataloguing key factors for plant growth—such as water availability,



⁶⁶ "Frequently Asked Questions Global Agro-Ecological Zoning version 4." Amazon S3, https://s3.eu-west-1.amazonaws.com/data.gaezdev.aws.fao.org/documentation/GAEZ4_FAQ.pdf. Accessed November 9, 2024.

solar energy, nutrient levels, and slope—AEZ mapping quantifies the types of crops and management practices that a given location can support. Traditionally, this analysis was data-intensive and infrequently updated. Today, geospatial AI techniques automate much of the process, continuously integrating new weather data and remote sensing observations to refine zone classifications. This yields up-to-date, high-resolution maps that guide what to plant where, and under which conditions to maximize yield while protecting the environment. A flagship example is the FAO's Global Agro-Ecological Zones (GAEZ) system which builds on this foundation by providing a standardized framework to analyze agricultural potential across different regions.⁶⁷ The latest version, GAEZ v4, offers significant technological improvements through advanced geospatial information, modern remote sensing, improved climatology, and AI integration.⁶⁸ GAEZ v4 delivers high-resolution mapping (approximately 0.9 x 0.9 km) that includes AEZ classifications, soil suitability assessments, terrain slope analysis, and land cover information. This system helps identify maximum potential crop yields, optimal crop types for specific areas, and best crop calendars for different regions.

Beyond land suitability zoning, AI also enhances environmental characterization by helping to identify and monitor the ecological conditions that influence agricultural viability. Machine learning models are now used to detect patterns in soil fertility, erosion risk, water availability, and vegetation cover by analyzing multi-source geospatial data, such as hyperspectral satellite imagery, LiDAR, and digital elevation models. AI-enabled classification systems help map degraded areas, salinized soils, and waterlogged zones, thereby providing crucial inputs for land restoration and sustainable intensification planning. Monitoring soil health, degradation patterns, and ecosystem resilience at scale has long been a challenge due to data gaps and monitoring costs. AI addresses this challenge by integrating field measurements, remote sensing, and predictive modeling into powerful diagnostic tools. In parallel, AI is playing an increasingly critical role in quantifying ecosystem services such as soil carbon storage—a key factor in land restoration, carbon markets, and climate-smart agriculture. Traditional methods for measuring soil organic carbon rely on physical sampling and lab testing, which are expensive and limited in coverage. AI-enabled approaches allow for rapid, scalable estimation of soil carbon by analyzing patterns in satellite imagery, terrain features, vegetation indices, and existing soil samples. These models can map carbon stocks across large landscapes and monitor changes over time, helping target interventions, validate restoration progress, and support emerging carbon credit programs with robust, low-cost monitoring systems.

High-Resolution Near-Term and Sub-Seasonal Weather Prediction

Agriculture is profoundly affected by weather variability, making improved forecasting one of the most cross-cutting AI applications in the sector. AI-powered weather prediction tools now deliver more localized and timely forecasts from the next hour to the next growing

⁶⁷ GAEZ v4 Data Portal, <https://gaez.fao.org/>. Accessed November 9, 2024.

⁶⁸ "Global Agro-Ecological Zones v4." FAO, March 10, 2022, <https://www.fao.org/gaez/home/video/global-agro-ecological-zones-vers-4/en>. Accessed November 9, 2024.

season. Using machine learning alongside numerical models, these systems learn from vast historical weather data and real-time sensor feeds to sharpen the accuracy of forecasts for specific locales. They excel at predicting short-term events like storms or dry spells that conventional models might miss, as well as at translating broad climate outlooks into village-level predictions. This granularity is especially valuable for farmers, who can adjust planting, irrigation, and harvesting schedules based on forecasts tailored to their fields. Likewise, agencies use such AI forecasts for early warning of floods or droughts to activate disaster preparedness plans in agriculture-dependent regions. Several major platforms exemplify this technology. IBM's The Weather Company supports smallholder farmers with hyperlocal weather forecasting through its Weather Data API, helping optimize decisions about planting, irrigation, and harvesting.⁶⁹ The platform uses IBM Watson to analyze satellite imagery, radar, and sensor data, thereby enabling farmers to better adapt to climate change.

Synthetic Data Generation

High-quality data are the fuel for AI solutions, yet in agriculture, real-world datasets are often scarce or incomplete—especially in emerging contexts or for new problems. Synthetic data generation addresses this gap by creating artificial but realistic datasets to train AI models. Using techniques like data augmentation and GANs, researchers can algorithmically produce additional training examples that mimic real agricultural data. This ability is particularly valuable for underrepresented scenarios (such as rare crop diseases or extreme weather events) where collecting extensive real images or records is difficult. By augmenting limited field data with synthetic examples, AI models become more robust and capable of handling the variability encountered in practice. In essence, synthetic data help to “teach” agricultural AI more comprehensively without waiting for years of new observations.

PlantVillage exemplifies this approach through its comprehensive digital platform, which houses information on over 150 crops and 1,800 diseases. At its core is a database of more than 50,000 expert-curated images showing both healthy and diseased crop leaves across 14 different species, including common crops like apple, corn, potato, and tomato. The platform covers a wide range of plant health issues, from fungal and bacterial diseases to viral infections and mite damage.⁷⁰ To enhance its disease detection capabilities, PlantVillage employs advanced data augmentation techniques and GANs. These methods expand the original dataset by creating variations of existing images through operations like rotation and flipping, as well as adding controlled noise. This synthetic data generation process helps create more robust AI models⁷¹ by exposing them to a broader range of potential scenarios, ultimately supporting farmers and researchers in their efforts to improve crop health and agricultural productivity.

69 Rylander (2021), <https://www.ibm.com/blogs/nordic-msp/helping-smallholder-farmers-predict-the-weather-can-transform-the-global-food-system/>. Accessed November 11, 2024.

70 Hughes and Salathé (2015), <https://doi.org/10.48550/arXiv.1511.08060>

71 Deshpande and Patidar (2023), <https://doi.org/10.1080/03235408.2023.2216359>

Knowledge Search, Query and Synthesis

The agrifood sector is knowledge-intensive, with valuable information scattered across research papers, technical reports, and local experiential knowledge. AI is helping to search, query, and synthesize knowledge from these vast sources, enabling stakeholders to get actionable answers without manually sifting through thousands of documents. Modern AI knowledge tools—often powered by large language models and semantic search algorithms—can ingest and index literature at scale and then respond to specific queries by locating relevant information and even summarizing it in plain language. This capacity is revolutionizing how agricultural scientists, extension officers, and policymakers access evidence and best practices. Instead of spending weeks conducting a literature review on, say, sustainable rice intensification, an AI assistant can retrieve the top findings and present a digest within seconds. For frontline advisors and farmers, such technology could mean instant answers to questions about pest management or market prices, drawn from trusted databases and guidance documents.

A concrete example is AGRIS (International System for Agricultural Science and Technology), managed by the FAO,⁷² exemplifies this approach through its comprehensive bibliographic database focused on agriculture and nutrition. With more than 13 million records of various publications, this free, open-access platform serves the global agricultural community by enabling sophisticated knowledge discovery. The system employs AI-powered search capabilities that use keywords, thesaurus terms, and metadata to improve the accuracy and relevance of search results. A key strength of AGRIS is its multilingual functionality, offering content in more than 100 languages. This feature ensures global accessibility, particularly benefiting non-English-speaking communities and international organizations like CGIAR.⁷³ The platform has further enhanced its capabilities by incorporating frontier technologies like AI and AGROVOC (FAO's multilingual thesaurus) to improve data integration and discovery. These AI systems help process large volumes of open data, enabling more contextual and comprehensive answers to questions about agriculture, climate change, and related topics.⁷⁴

Field Boundary Delineation for Farmer Profiles

An estimated 570 million farms exist worldwide, and most of them are small and fragmented. Accurately mapping the field boundaries of these farms is foundational for a host of digital agriculture services from agronomic advisory and input delivery to crop insurance and credit profiling. Knowing the precise geospatial extent of each farmer's plot enables crop monitoring, yield estimation, and tailored recommendations at the field level. It also feeds into supply chain and policy planning (for example, estimating production from a cluster of fields or targeting subsidies to specific plots). Traditionally, field mapping was done via surveys or manual digitization of satellite images, a process that is laborious and often impractical at scale. AI has

72 Jani, et al. (2024), <https://alliancebioversityciat.org/stories/enhancing-agricultural-research-fao-agris-agrovoc-programs-conversation-elizabeth-arnaud>. Accessed November 8, 2024.

73 CGIAR, <https://www.cgiar.org/>

74 Bravo (2020), <https://aims.fao.org/zh/webinars/agris-webinar-using-artificial-intelligence-ai-data-discovery-and>

stepped in to automate field boundary delineation by analyzing satellite imagery to detect the edges of cultivated parcels. This is a complex vision task—fields can be irregularly shaped, boundaries may be obscured by vegetation or adjacent fallow land, and what constitutes a “field” can vary by landscape. Nevertheless, advanced convolutional neural networks (often using U-Net or similar architectures) have shown remarkable success in distinguishing field versus non-field patterns in high-resolution imagery. The result is rapidly updated digital maps of farm plots, even in smallholder-dominated regions.

One cutting-edge solution is DigiFarm, a platform that combines AI models with satellite data to produce precise field outlines. The platform processes super-resolved Sentinel satellite imagery to create accurate field boundaries, offering historical data dating back to 2015 and providing regular in-season updates.⁷⁵ Its deep neural network models can detect field boundaries at resolutions ranging from 10 meters to 1 meter per pixel—a crucial capability given that 83 percent of global agricultural fields are smaller than 2 hectares.⁷⁶ The platform delivers these data through an API for easy integration with other digital agricultural tools, while also providing digital editing capabilities that allow users to refine field boundaries by splitting, merging, or adjusting field details.⁷⁷ Through these features, DigiFarm helps farmers optimize field productivity, particularly during seeding operations, leading to improved crop yields and more efficient use of resources such as fertilizer. This technology makes precision agriculture more accessible to farms of all sizes, supporting more sustainable and efficient agricultural practices.



75 Oracle Blogs (2022), <https://blogs.oracle.com/cloud-infrastructure/post/to-help-farmers-get-more-from-their-fields-digifarm-runs-its-precision-agriculture-platform-on-oci>. Accessed November 11, 2024.

76 Business Norway (2023), <https://businessnorway.com/solutions/digifarm-delivers-deep-neural-networks-and-remote-sensing-for-higher-crop-yields>. Accessed November 11, 2024.

77 DigiFarm, <https://digifarm.io/products/field-boundaries>. Accessed November 11, 2024.

04

Investment Priorities

Realizing the potential of AI technologies requires strategic investments across several interconnected domains. This chapter outlines the key investment priorities that can accelerate the development, adoption, and impact of AI in agriculture, with special emphasis on supporting SSPs and addressing global food security challenges.



Agriculture-Specific AI Models and Capacity

The advancement of AI in agriculture depends critically on both the adaptation of foundational models and the development of specialized models for agricultural applications. While general-purpose LLMs provide powerful capabilities, they require significant fine-tuning and adaptation for agricultural contexts. Agriculture-specific AI models require targeted investment to address the unique challenges of farming systems across diverse geographical and climatic contexts (figure 6.1). The development of specialized models tailored to agriculture demands significant resource allocation focused on contextual adaptation; many existing AI architectures requiring substantial modification to account for farming's biological complexity and weather dependencies

Figure 4.1. Taxonomy of key components for AI Advisory to scale



Source: Gates Foundation (2025)

The democratization of agricultural AI models requires investment in making technologies accessible to diverse stakeholders, from large commercial operations to smallholder farmers with limited resources. Investments in model compression and distillation techniques can enable sophisticated AI to run on more affordable hardware, mirroring the broader trend where Meta's Llama 3 8B model performs comparably to the previous Llama 2 70B model, despite being nearly one-tenth the size.⁷⁸ Funding for agricultural AI education and capacity building among farmers, extension workers, and local technicians represents a critical investment priority that can multiply the impact of hardware and software expenditures across agricultural communities. Companies like AGEYE Technologies, which received investments

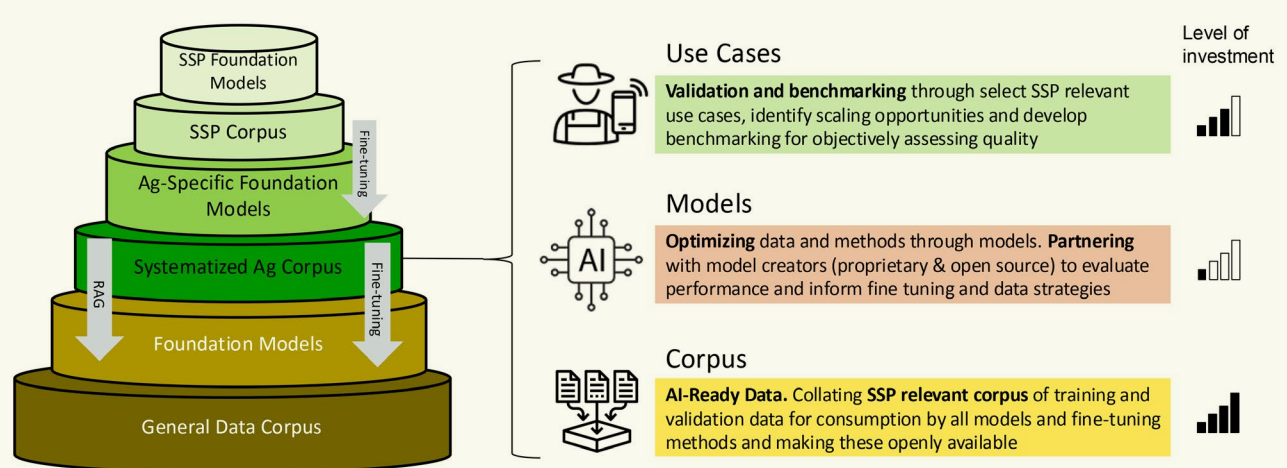
⁷⁸ Jaipuria (2024), <https://www.wing.vc/content/plummeting-cost-ai-intelligence>

from Nouryon, demonstrate how specialized agricultural AI platforms that convert visual inputs into crop-growth insights can create actionable intelligence specifically designed for indoor farming environments.⁷⁹

Foundational Models versus Domain-Specific Fine-Tuning

Investment in agriculture-specific AI requires a multi-layered approach that balances leveraging existing foundational models with developing specialized capabilities for agriculture. The pyramid approach to agricultural AI model development illustrates this strategic investment framework:

Figure 4.2. Hierarchy of AI model development for agriculture, showing the progression from general models to specialized agricultural applications



Source: Gates Foundation (2025)

As the ecosystem evolves from general-purpose foundational models toward increasingly specialized fine-tuning for agricultural contexts, benchmarking and model evaluation become essential. Understanding what constitutes ‘quality’ or ‘accuracy’ is highly context-specific, varying not only by crop type and agroecological zone, but also by language, local farming practices, and even infrastructure constraints. Developing robust, transparent benchmarks is therefore critical for ensuring models are both effective and equitable across diverse LMIC settings.

⁷⁹ Jaipuria (2024), <https://www.wing.vc/content/plummeting-cost-ai-intelligence>

Investment priorities for model development include:

- **Agriculture-Specific Foundation Models:** Rather than building completely new LLMs from scratch, significant return on investment can be achieved by fine-tuning existing foundation models on agricultural data. These “AgLLMs” would incorporate domain knowledge about crops, livestock, soil science, and farming practices.
- **Systematic Agricultural Corpus:** Creating comprehensive datasets of agricultural knowledge is essential for effective fine-tuning. This process includes digitizing research papers, extension manuals, traditional farming knowledge, and crop-specific information in multiple languages.
- **RAG Infrastructure:** Investments in RAG systems that connect LLMs to trusted agricultural knowledge bases can significantly improve the accuracy and relevance of AI outputs without requiring constant retraining.
- **Fine-Tuning Methods:** Research into efficient fine-tuning techniques specifically for agricultural applications can reduce the computational resources needed while improving model performance on specialized tasks.

Agriculture-Specific Corpus Development

Building high-quality datasets for training and fine-tuning AI models is perhaps the most critical investment area. Key priorities include:

- **Multi-Modal Agricultural Data:** Investments in collecting, curating, and annotating diverse data types, including text, images, audio for voice-based interfaces, and sensor readings that represent the full spectrum of agricultural knowledge.
- **Low-Resource Language Coverage:** Dedicated funding for developing agricultural datasets in underrepresented languages to ensure AI benefits reach farmers who speak regional and local languages.
- **Standardized Data Formats:** Development of common data formats and annotation standards specifically for agricultural data to enable interoperability and model transferability.

Foundational Data Investments

Foundational data infrastructure represents perhaps the most critical investment priority for AI in agriculture, as even the most sophisticated algorithms cannot overcome fundamental data limitations. Comprehensive soil mapping initiatives, weather station networks, and crop performance databases require substantial upfront investment; however, they create

79 Nouryon (2025), <https://www.nouryon.com/sustainability/grow/investing-in-agricultural-artificial-intelligence-with-ageye/>

enduring value across multiple AI applications, with AI algorithms helping determine soil composition, nutrient content, and crop selection suitability for specific plots. The integration of diverse agricultural data streams—from satellite imagery and drone surveillance to IoT field sensors and historical yield records—demands investment in standardized data formats, interoperability protocols, and secure data sharing frameworks. In SSP contexts, where agricultural data fragmentation presents a significant barrier, investments in unified agricultural data platforms can create disproportionate value by connecting previously siloed information sources from various regional agencies and research institutions.

Data collection technologies tailored to agricultural contexts require focused investment, particularly for environments where standard data gathering approaches face challenges. Investments in low-cost, ruggedized IoT sensors capable of withstanding harsh field conditions and operating with minimal maintenance represent a high-priority funding area that can dramatically expand the data foundation for agricultural AI. PPPs for data sharing present another promising investment avenue, enabling the creation of comprehensive agricultural data commons while respecting farmer privacy and intellectual property considerations.

The Consultative Group on International Agricultural Research (CGIAR)-led AgPile initiative focuses on creating a federated platform for global agricultural data integration. Supported by the Gates Foundation, AgPile aggregates regionally relevant datasets into an AI-ready corpus that adheres to FAIR principles (Findable, Accessible, Interoperable, Reusable). This platform enables researchers to access high-value datasets for innovations, such as disease detection and phenotypic analysis using AI tools. By fostering collaboration across research institutions globally, AgPile accelerates the development of solutions tailored to smallholder farming systems

In Rwanda, eSoko⁸⁰ is a government-led agricultural market information system designed to empower farmers by providing real-time market price data and other relevant information through Information and Communication Technologies (ICTs). The system aims to help farmers make more informed decisions about when and where to sell their produce, ultimately improving market efficiency and farmer incomes

Kenya's Integrated Agriculture Management Information System (KIAMIS)⁸¹ platform is a prime example of foundational data investment aimed at improving agricultural service delivery. Developed with support from FAO, KIAMIS integrates farmer registries, subsidy management modules, and agro-meteorological data into a centralized system. It has registered over 130,000 farmers and piloted e-voucher systems to streamline access to inputs like fertilizers and seeds. By digitizing land records and creating a unified farmer registry, KIAMIS enables targeted interventions while reducing inefficiencies in subsidy distribution.

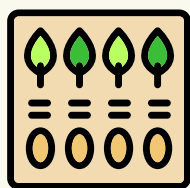
80 <https://rwanda.lsc-hubs.org/cat/collections/metadata:main/items/esoko-gov-rw>

81 <https://kiamis.kalro.org/>

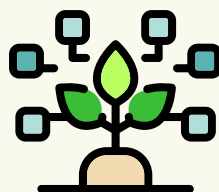
Key Components of Foundational Data Investments



**Farmer
Registries**



**Geospatial
Mapping**



**Interoperability
Standards**



**Data Privacy
Frameworks**

By investing in these foundational systems, governments and organizations can create an enabling environment for sustainable agricultural AI applications that enhance productivity while addressing environmental challenges.

Compute Infrastructure Investments

Compute infrastructure tailored to agricultural contexts represents a crucial investment frontier, particularly as AI model sophistication increases computational demands. Edge computing solutions that bring AI processing capabilities directly to farms rather than rely exclusively on cloud infrastructure demand strategic investment. Investments in specialized AI hardware optimized for agricultural applications—including weather-resistant, power-efficient processors capable of operating in remote farming environments—can dramatically expand AI accessibility across diverse agricultural settings. Cloud computing resources dedicated to agricultural AI processing represent another key investment priority, particularly for compute-intensive applications like large-scale crop simulation, climate impact modeling, and genetic optimization algorithms. Rural connectivity infrastructure remains a foundational investment requirement, as the digital divide continues to limit AI adoption in many agricultural regions. Funding for AI-ready hardware lending libraries and shared computing resources can democratize access for smaller farms and agricultural organizations lacking capital for significant technology infrastructure. Strategic investments in agricultural research institution computing capacity not only advance scientific progress but also create regional centers of expertise capable of supporting broader agricultural AI adoption and adaptation.

National AI Stacks and Agricultural Data Exchange

Several countries are developing national AI infrastructure to support domain-specific applications:

- **India's AI Stack Approach:** Following India's model of developing an agricultural component within national digital infrastructure, with integrated data exchange capabilities.
- **Agricultural Open Networks:** Investing in open protocol networks like the example from Uttar Pradesh that enable multiple AI service providers to plug into standardized agricultural data exchanges.

India's AI Stack: A Model for National AI Infrastructure Investment

India's comprehensive approach to building national AI infrastructure through the IndiaAI Mission provides an instructive model for agricultural AI development. Launched in March 2024 with a budget of ₹10,371.92 crore, the mission demonstrates how coordinated government investment can create the foundation for AI innovation across sectors, including agriculture.

Key Components of India's AI Stack:

- **IndiaAI Compute Portal:** Provides access to over 18,000 GPUs at affordable rates (₹67 per GPU hour), enabling researchers, startups, and government departments to develop and deploy AI models without prohibitive infrastructure costs. The portal features high-end GPUs including AMD MI300X, Nvidia H200/H100, and Intel Gaudi 2, facilitating the development of indigenous AI models trained on Indian datasets.
- **AIKosha Dataset Platform:** Comprises an all-inclusive repository of datasets, models, and use cases with sandbox capabilities—safe, test-ready environments—through an integrated development environment. For agricultural AI development, it hosts non-personal data from the agriculture ministry, enabling the training of contextually relevant models.
- **AI Competency Framework:** Equips public sector officials with the skills necessary to effectively engage with AI technologies, addressing key concerns such as data privacy and cybersecurity. This framework emphasizes behavioral, functional, and domain-specific competencies essential for policymakers and regulators.
- **Support Programs for AI Innovation:** Includes the IndiaAI Startups Global Acceleration Program in collaboration with Station F and HEC Paris, the IndiaAI Fellowship for students, and innovation challenges such as the IndiaAI Innovation Challenge.

This integrated approach to AI infrastructure investment demonstrates how countries can build national capacity for agricultural AI applications. Such national infrastructure investments can significantly accelerate the development and adoption of AI in agriculture. By providing accessible compute resources, agriculture-specific datasets, skills development, and innovation support.

Regional Compute Facilities

Addressing the computational divide requires the following strategic investments in accessible computing resources:

- **Agricultural AI Hubs:** Establishing regional centers of excellence with specialized computing infrastructure for agricultural AI development and deployment.
- **Green Compute for AI:** Investing in energy-efficient computing infrastructure powered by renewable energy to ensure that AI's environmental footprint does not counteract its benefits in agriculture.
- **Edge Computing Solutions:** Developing specialized hardware for agricultural edge devices that can run AI models locally to reduce connectivity requirements for remote farms.

Investments in use case-specific applications of AI in agriculture needs to focus on creating scalable, sustainable, and inclusive solutions that address the unique challenges of agricultural systems. These investments should be structured to support the entire lifecycle of AI innovations, from ideation to scaling, ensuring that technologies are not only developed but also effectively deployed and adopted by end users. This section explores three critical areas of investment: Pilot and MVP Sandboxes, Scale-Up Mechanisms, and Sustainable Deployment Models, with examples and insights into their transformative potential.

Pilot and MVP Sandboxes: Creating Testing Grounds for Innovation

Investing in pilot programs and MVP sandboxes is essential to test AI applications in real-world agricultural contexts. These initiatives allow innovators to experiment with new technologies under controlled conditions, gather feedback, and refine solutions before large-scale deployment. Regulatory sandboxes, such as those implemented in Kenya for agricultural data governance, provide a framework for testing innovative AI solutions while ensuring compliance with local regulations. For instance, the AIEP, demonstrates the value of MVP sandboxes. This initiative supports the development of AI-driven advisory tools tailored to smallholder farmers in Kenya and India. By enabling real-time, contextual advice through chatbots and voice-based systems, AIEP fosters innovation while addressing challenges like language barriers and limited digital literacy. The platform's iterative development process—delivering monthly increments based on user feedback—ensures that solutions are both practical and scalable. Investments in such sandboxes should prioritize the following:

- **Localized Data Collection:** Ensuring that MVPs are trained on region-specific datasets to enhance relevance.
- **User-Centric Design:** Engaging farmers and extension agents in co-creation processes to align solutions with their needs.
- **Interoperability Standards:** Developing open protocols to integrate MVPs with existing agricultural systems.



Scale-Up Mechanisms: Expanding Proven Solutions

Once pilot projects demonstrate viability, investments need to focus on scaling up these solutions to reach broader agricultural communities. Scaling requires significant resources for infrastructure development, capacity building, and stakeholder engagement. PPPs play a crucial role in this phase by combining government support with private sector expertise.

For example, India's Saagu Baagu initiative successfully scaled precision farming technologies for chili farmers in Telangana. By leveraging AI-powered tools for pest management and irrigation optimization, the program increased yields by 21 percent while reducing input costs. Scaling efforts included training programs for farmers, subsidies for technology adoption, and partnerships with local agribusinesses to ensure market access. Key investment priorities for scaling include:

- **Infrastructure Development:** Building DPI, such as farmer registries and data exchange platforms.
- **Capacity Building:** Training extension workers and farmers to use AI tools effectively.
- **Market Linkages:** Establishing supply chain networks to connect farmers with buyers and input providers.

Sustainable Deployment Models: Ensuring Long-Term Impact

Sustainability is critical for the long-term success of AI applications in agriculture. Investments need to focus on creating business models that ensure financial viability while delivering social and environmental benefits. Subscription-based services, pay-as-you-go models, and revenue-sharing agreements are some approaches that can make AI solutions affordable for smallholder farmers. In Uttar Pradesh, India, an Open Network for Agriculture integrates farmer identity systems with AI-powered advisory services. This model ensures sustainability by aligning incentives across stakeholders—farmers receive personalized advice at minimal cost, while service providers gain access to a large customer base through a unified platform. Early results indicate a 10–15 percent increase in farmer profits due to improved market linkages and reduced input costs. Sustainable deployment also requires the following:

- **Energy-Efficient Technologies:** Developing low-power AI models suitable for rural settings.
- **Inclusive Design:** Ensuring that marginalized groups, such as women farmers, benefit equally from AI solutions.
- **Policy Support:** Establishing governance frameworks that promote fair access and prevent monopolization of AI resources.

Investments in use case-specific applications must be strategically structured across the innovation lifecycle—starting with pilot sandboxes to test feasibility, scaling proven solutions through robust infrastructure and partnerships, and ensuring sustainability through inclusive business models. By aligning these investments with localized needs and global best practices, stakeholders can unlock the transformative potential of AI in agriculture while fostering resilience, equity, and sustainability across farming systems.

Policy and Governance Investments

Policy and regulatory frameworks for agricultural AI require substantial investment to ensure responsible innovation that benefits all stakeholders. Funding for comprehensive agricultural AI policy development—including data governance standards, algorithmic transparency requirements, and accountability mechanisms—creates the foundational conditions for sustainable investment across other priority areas. Ethical oversight mechanisms specific to agricultural AI applications demand dedicated investment, particularly as complex questions emerge around data ownership, algorithmic bias, and the distribution of AI benefits across diverse farming communities. Investment in participatory governance structures that ensure farmer and community voices in agricultural AI decision-making represents a critical priority for building trust and ensuring that technologies address actual rather than presumed needs.

MahaAgri-AI Policy 2025-2029

Maharashtra has launched an ambitious policy framework to position itself as a national leader in AI-driven agriculture, with an initial allocation of 500 crore⁸². The policy establishes a comprehensive Digital Public Infrastructure (DPI) that includes an Agriculture Data Exchange (ADeX), AI-enabled sandbox environments for testing solutions, a remote sensing and geospatial intelligence engine, and an agri-food traceability platform. Governed by a State-Level Steering Committee and supported by a dedicated AI and Agritech Innovation Centre, the policy adopts a phased implementation approach spanning foundation-building, pilot testing, statewide scale-up, and cross-sector replication. The framework specifically targets persistent agricultural challenges including low productivity, climate variability, and water stress through technology-driven interventions across the entire agricultural value chain.

The policy promotes a dual-track approach to innovation: providing incubation support for novel AI ideas from startups and research institutions, while facilitating the scaling of proven technologies through financial assistance directly to farmers via DBT mode. Four State Agricultural Universities will establish AI Research and Innovation Centers to serve as hubs for developing GenAI and emerging technology solutions in collaboration with industry partners. Key initiatives include the VISTAAR program for multilingual, AI-powered farmer advisories, capacity-building programs for over 13,000 extension workers, and an annual Global AI in Agriculture Conference to attract investment and partnerships. The policy emphasizes ethical AI deployment, farmer-centric design, public-private partnerships, and measurable impact assessment, with a mid-term review planned after three years to adapt to the rapidly evolving AI landscape.

82 http://agritech.tnau.ac.in/pdf/Maha%20Agri-AI%20Policy%202025%E2%80%932029_English_250619_104818.pdf

Cross-border cooperation mechanisms on agricultural AI demand strategic investment, particularly as global food systems interconnections intensify. Targeted funding for agricultural AI impact assessment methodologies can establish evidence-based approaches to evaluating benefits, risks, and unintended consequences—information crucial for guiding future investment prioritization. Investment in anti-monopoly and competition frameworks specific to agricultural AI can prevent harmful concentration of technological power while encouraging innovation and affordability. The European Partnership Agriculture of Data exemplifies needed investment in guiding strategies for technology development while considering the social and ethical impacts of AI integration, recognizing that strong policies need to prioritize transparency, fairness, and accountability.

Creating an enabling environment for AI in agriculture requires strategic policy investments:

- **AI-Ready Agricultural Policies:** Supporting countries in developing comprehensive policies that balance innovation with protection of farmer interests.
- **Data Governance Frameworks:** Investing in agricultural data governance mechanisms that ensure data sovereignty while enabling innovation.
- **Ethical AI Guidelines:** Developing sector-specific ethical standards for agricultural AI that address unique considerations like food security and environmental impact.

As the cost of AI intelligence continues its dramatic downward trajectory, strategic allocation of investment across these priority areas will determine whether agricultural AI fulfills its potential to create more productive, sustainable, and equitable food systems. The most successful investment approaches will likely combine targeted technological funding with complementary investments in human capacity, institutional development, and policy frameworks—recognizing that agricultural AI's transformative potential depends not only on algorithms and computing power; but also on the broader systems in which these technologies are embedded.

Forward Look: Advancing Agrifood Transformation through Responsible AI

This report has outlined a structured approach to understanding how artificial intelligence (AI) can contribute to transformation across agrifood systems. It has explored a range of AI applications—from early-stage crop discovery to last-mile service delivery—and identified critical enablers, barriers, and investment priorities likely to influence the trajectory of agricultural innovation, particularly in low- and middle-income countries.

Looking ahead, one message is clear: digital tools, including AI, are expected to play an increasingly important role in the future of agriculture. That future, however, will not be evenly distributed unless we act deliberately to shape it. While AI holds immense promise to drive productivity, enhance climate resilience, reduce resource waste, and improve livelihoods, it will only deliver these benefits if embedded within a broader ecosystem that prioritizes inclusivity, sustainability, and long-term capacity building.

Several emerging trends will define the road ahead. First, agricultural AI must be tailored to local contexts—technically, linguistically, environmentally, and culturally. The development of agriculture-specific models that reflect local farming systems, crops, languages, and data realities is not simply a technical challenge—it is also a social imperative. Without inclusive design, AI risks reinforcing rather than reducing structural inequalities in food systems.

Second, the quality, availability, and governance of data will be central to AI's effectiveness. Foundational agricultural datasets—covering soil health, weather, pest dynamics, market prices, and more—remain fragmented, inaccessible, or poorly maintained in many countries. Investing in data infrastructure that is open, interoperable, and representative of the diverse realities of SSPs will be essential. These datasets must also reflect indigenous knowledge and be co-owned by communities that contribute to them.

Third, AI needs infrastructure—both digital and human. Cloud access, compute power, and affordable connectivity are necessary for AI models to be deployed effectively in rural settings. Equally critical is the development of human capital across the ecosystem: not only AI developers and data scientists, but extension workers, agronomists, policy actors, and farmers who can engage with and shape these tools meaningfully. AI must be demystified, localized, and democratized.

Fourth, innovation alone is not enough—scaling impact requires systems integration. The true power of AI lies in its ability to connect advisory services with financial inclusion, supply chain logistics, risk mitigation, and policy planning. For this to happen, PPPs must be cultivated, regulatory frameworks must evolve, and investment must flow into both frontier technologies and foundational enablers, such as governance, trust-building, and policy capacity.

Fifth, and perhaps most importantly, AI must be guided by values. As algorithms increasingly influence decisions about resource allocation, pricing, creditworthiness, and risk,

we must ensure these systems are accountable, transparent, and aligned with the public good. Ethical frameworks, participatory design processes, and rights-based governance models are not optional—they are essential to ensuring that AI in agriculture supports equity and resilience.

Call to action

AI in agriculture is no longer an aspirational concept - it is already demonstrating tangible impact. Yet the distribution of its benefits remains highly uneven. Most small-scale producers in low- and middle-income countries (LMICs) continue to operate without access to AI-enabled tools - not due to a lack of viable solutions, but because the investment required to scale them has not yet been mobilized at the level or coordination needed. The era of fragmented pilot projects must give way to a new phase of system-wide implementation. What is now required is a coherent, cross-sectoral investment agenda focused on core enablers: context-specific AI models, interoperable and trusted datasets, inclusive compute and connectivity infrastructure, participatory design approaches, and robust governance frameworks

Financing this agenda demands clarity of roles. Governments can invest public resources in digital public goods, foundational data systems, and farmer extension services. Development banks and bilateral donors can provide concessional and blended finance to de-risk early-stage projects, particularly in LMICs, while ensuring equity and sustainability are prioritized. Research institutions can direct funding toward open datasets, agriculture-specific AI models, and human capacity development. The private sector should mobilize venture and corporate capital to scale proven solutions, strengthen last-mile distribution, and develop inclusive business models that reach small-scale producers.

Collaboration across these actors will be essential to create a resilient and inclusive ecosystem. Governments, development partners, researchers, and private companies must pool resources to support farmer-centered innovation, expand equitable access to computational power, and scale evidence-based solutions that have demonstrated impact. AI holds the potential to improve agricultural productivity, enhance climate adaptability, and reduce inequalities—but realizing this potential requires immediate, coordinated, and sustained financing commitments. The future of global food security and climate resilience may hinge on whether these stakeholders act together - and act now.

Appendix

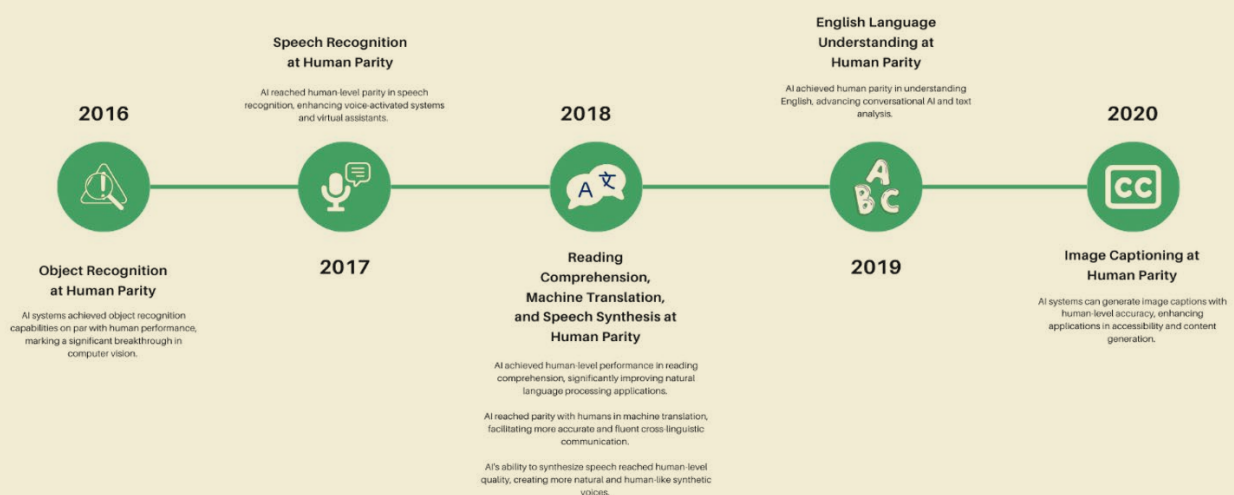


Appendix 1. Demystifying Artificial Intelligence

AI refers to the ability of machines or computer systems to mimic human-like intelligence and perform tasks that typically require human cognition, such as learning, reasoning, problem-solving, perception, and decision-making. AI has a rich history dating back to the mid-20th century and evolving through various milestones and inflection points. The formal inception of AI as a field of study is generally marked by the seminal 1956 Dartmouth Summer Research Project on Artificial Intelligence, organized by John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon. This event brought together researchers enthusiastic about creating machines capable of reasoning, learning, and problem-solving. Early efforts focused on symbolic AI, where human knowledge was encoded into explicit rules to enable machines to perform tasks like playing chess and solving algebraic problems.

During the 1950s, the era of rule-based systems saw the emergence of expert systems that allowed for the imitation and automation of very narrow human tasks. Although limited, these systems represented significant progress in AI as they could perform specific tasks by following predefined rules. Training computation scale during this period approached 100 million floating-point operations per second (FLOPs), highlighting the growing computational power available to researchers.

Figure A1.1. Evolution of Artificial Intelligence



Source: Authors

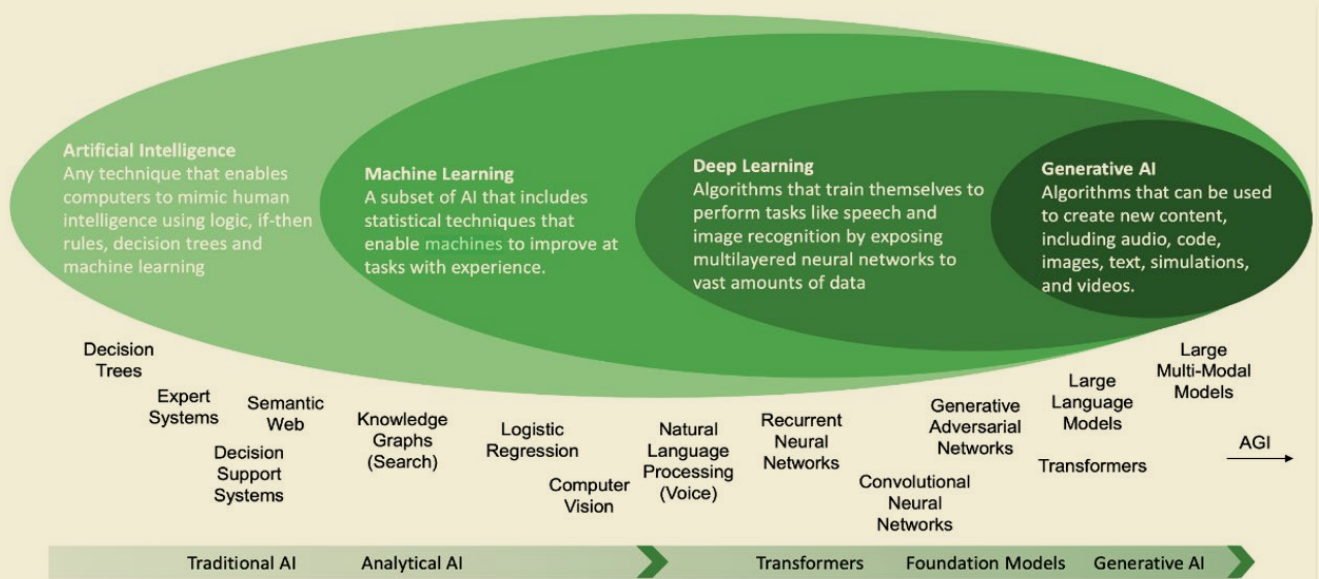
The initial optimism of AI research soon met with the reality of computational limitations and the complexity of human intelligence. The 1970s and 1980s saw “AI winters,” characterized by reduced funding and interest due to unmet expectations. Despite these setbacks, the field persisted, evolving through innovations in algorithms, increased computational power, and the advent of machine learning. The 1980s, known as the era of statistical learning, marked a significant turning point with the rise of techniques that enabled models to learn from data and understand narrow categories of patterns and classifications. The training computation scale reached approximately 1 petaFLOP (quadrillion FLOPs), reflecting the enhanced capabilities of AI systems.

The early 21st century brought about a renaissance in AI research, driven by the explosion of big data, advancements in computing hardware, and the development of sophisticated algorithms. The 2000s, referred to as the era of advanced learning, saw the advent of more sophisticated learning models, particularly deep learning, which achieved higher accuracy for complex learning and prediction tasks. The training computation scale increased dramatically to around 100 million petaFLOPs, enabling the handling of vast and complex datasets. This led to significant breakthroughs in image and speech recognition, natural language processing, and autonomous systems. Several key inflection points have marked the evolution of AI in recent years. While these milestones represent significant achievements in AI’s capabilities, 2022 marked a truly transformative inflection point. In that year, the focus shifted to GenAI, with models capable of generating new multimodal, human-like content by training on vast amounts of public internet data. The training computation scale now exceeds 10 billion petaFLOPs, highlighting a new era of AI poised to revolutionize industries, improve efficiency, and enhance human capabilities in unprecedented ways.

Components of Artificial Intelligence

To truly understand AI, it is crucial to recognize that it is not a single technology but a field encompassing various interconnected components and approaches. The foundation of AI in agriculture began with rule-based systems, logical frameworks, and decision support tools. These traditional AI applications continue to serve important functions in the agricultural sector through expert systems, decision support systems, and semantic web technologies. Decision trees, shown at the bottom of this category (figure A1.2), have proven particularly valuable for agricultural classification tasks and decision-making processes

Figure A1.2. Artificial Intelligence Landscape



Source: Authors

Machine learning is a field of AI that enables computers to learn from data without being explicitly programmed. It involves the development of algorithms that can automatically detect patterns in data, make decisions, and improve their performance over time through experience. Machine learning is often categorized into three types: supervised learning, unsupervised learning, and reinforcement learning (RL).

- **Supervised learning:** models are trained using labeled data. This technique is widely applied in agriculture for crop yield prediction, disease detection, and livestock management. For example, researchers have used supervised learning models, like Random Forests and Support Vector Machines, to predict crop diseases based on labeled images of infected plants.⁸³ Supervised learning can also enhance supply chain optimization and track perishable foods to reduce waste.⁸⁴
- **Unsupervised Learning:** This does not rely on labeled data and can find hidden patterns in the data. This approach is crucial for tasks such as analyzing soil data, clustering different crop types based on soil properties, and segmenting weed species in large datasets without prior labels.⁸⁵ This technique is also useful in anomaly detection and can help identify irregularities in irrigation systems or detect outliers in crop growth patterns.⁸⁶

83 Liakos et al. (2018), <https://doi.org/10.3390/s18082674>.

84 Pallathadka et al (2022), <https://doi.org/10.1109/icacite53722.2022.9823427>.

85 Ferreira et al. (2019), <https://doi.org/10.1016/J.COMPAG.2019.104963>.

86 Dike et al. (2018), <https://doi.org/10.1109/CBS.2018.8612259>.

- **RL:** RL focuses on how agents act in an environment to maximize cumulative rewards over time. The agent learns by interacting with the environment, receiving feedback in the form of rewards or penalties based on its actions, and adjusting its behavior to maximize rewards. Unlike supervised learning, which produces immediate outputs, RL involves long-term decision-making (sequential), in which the agent must balance immediate rewards with future gains.⁸⁷ For example, an RL agent can be used in crop management to optimize fertilizer use, especially nitrogen, balancing yield and environmental impacts through data-driven decision-making.⁸⁸

Deep Learning, a subset of machine learning, uses artificial neural networks inspired by the human brain to process data and make decisions. These networks consist of multiple layers, allowing them to handle more complex tasks and recognize more nuanced patterns than traditional machine learning approaches. An example of deep learning in action is image recognition technology, which can identify objects, faces, or even plant diseases in photographs with remarkable accuracy. Neural networks are a machine learning model inspired by the structure and function of the human brain. Just like the brain has interconnected neurons that transmit signals, neural networks have interconnected nodes (artificial neurons) that transmit data and perform computations. The most basic neural network architecture is the feedforward neural network, which consists of an input layer, one or more hidden layers, and an output layer. Each layer comprises nodes, and the nodes in adjacent layers are connected by weights that determine the strength of the connections.

A simple analogy will help to explain how these networks work: Imagine you are trying to predict whether it will rain based on specific weather conditions, such as temperature, humidity, and wind speed. These weather conditions are the inputs to the neural network. The input layer receives and passes these inputs to the first hidden layer. Each node in the hidden layer calculates the inputs, combining them with weights and an activation function (like a mini formula). These nodes are little workers that process the weather data based on their specific jobs. The outputs from the first hidden layer are then passed to the next hidden layer (if there are multiple hidden layers), where another set of calculations is performed. This process continues through all the hidden layers, with each layer extracting more complex features and patterns from the data. Finally, the outputs from the last hidden layer are passed to the output layer, which combines them to produce the final prediction—in this case, whether it will rain or not. During training, the neural network adjusts the weights between the nodes to minimize the prediction error on known examples (training data). This process is like fine-tuning the workers' jobs and the connections between them to improve their collective performance.

⁸⁷ Sasakawa, Hu and Hirasawa (2006), <https://doi.org/10.1541/IEEJEISS.126.1165>.

⁸⁸ Kallenberg et al. (2023), <https://doi.org/10.1017/eds.2023.28>.

Different neural network architectures, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have specialized structures and calculations tailored to specific data types, such as images or sequences. The power of neural networks lies in their ability to automatically learn complex patterns and representations from data without needing explicit programming of rules or feature engineering. This makes them highly effective for AI tasks like image recognition, natural language processing, and decision-making. However, neural networks can be opaque (like a black box), making it difficult to understand exactly how they arrive at their predictions. Ongoing research aims to make them more interpretable and trustworthy for critical AI applications.

Understanding Neural Networks in Agriculture: the Case of Cassava Disease Detection⁸⁹

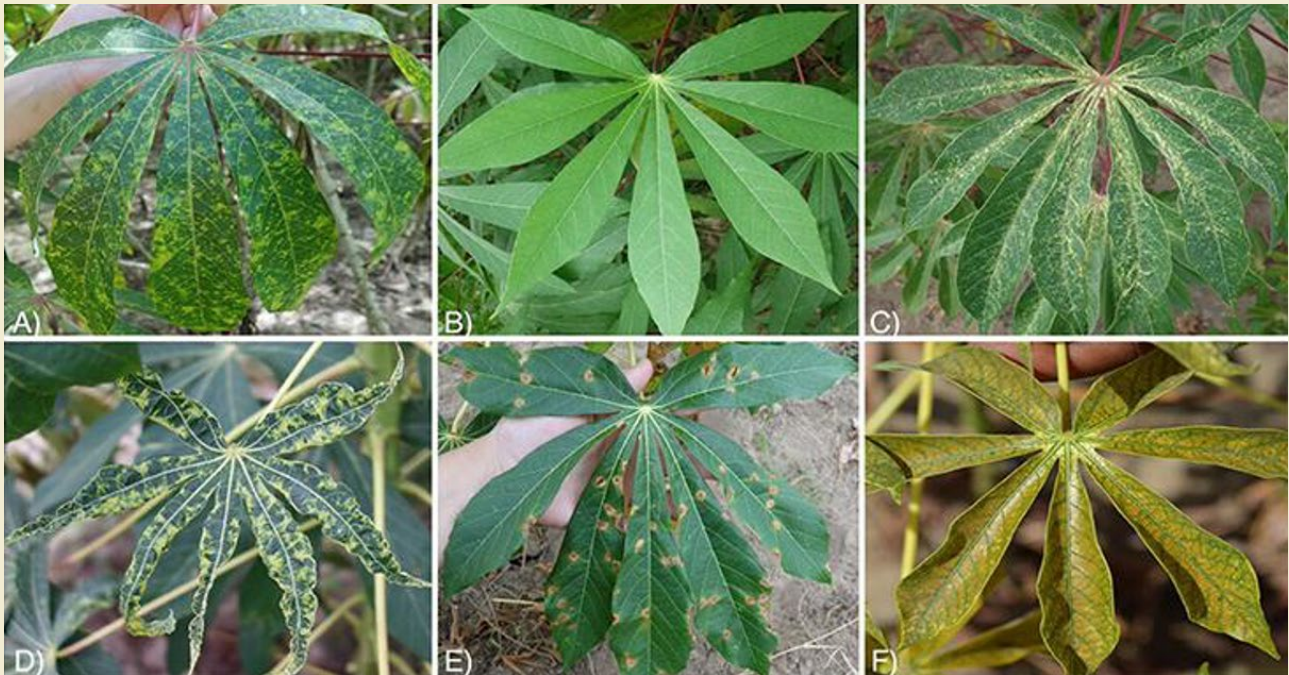
Neural networks function like the human brain's interconnected neurons but in a simplified, digital form. When applied to cassava disease detection, this technology creates a powerful diagnostic tool that can identify devastating crop diseases with expert-level accuracy.

A neural network for cassava disease detection processes information through distinct layers:

- **Input Layer:** The system begins by receiving a digital image of a cassava leaf. This image is converted into thousands of numerical values representing pixel colors and patterns. The input layer captures the raw visual data, just as a farmer might first examine a leaf's overall appearance.
- **Hidden Layers:** Multiple processing layers analyze the image in increasing levels of abstraction. Early layers detect basic features like edges, spots, and color variations on the leaf. Deeper layers combine these features to identify more complex patterns associated with specific diseases, such as the distinctive mosaic pattern of Cassava Mosaic Disease (CMD) or the yellow leaf discoloration characteristic of Cassava Brown Streak Disease (CBSD).
- **Output Layer:** The final layer classifies the image into specific categories, such as "healthy," "CMD," "CBSD," or "bacterial blight," providing farmers with a specific diagnosis.

Figure A1.3. Provides examples of images with in-field backgrounds from six classes in the original cassava dataset (three disease classes, two mite damage classes, and one healthy class without disease or damage).

(A) Cassava brown streak disease (CBSD), (B) Healthy plants, (C) Green mite damage (GMD), (D) Cassava mosaic disease (CMD), (E) Brown leaf spot (BLS), (F) Red mite damage



Source: Deep Learning for Image-Based Cassava Disease Detection

Researchers developed an effective cassava disease detection system by training neural networks with over 2,500 images of cassava leaves showing various health conditions. During training, the network:

- Examines a labeled image, for example, “This leaf has CMD”.
- Compares its prediction with this known label.
- Adjusts internal connections to improve accuracy.
- Repeats this process thousands of times with different examples.

This training process enabled the system to achieve 93 percent accuracy in identifying cassava diseases, including CMD, CBSD, and bacterial blight—conditions that can devastate this critical food crop in Sub-Saharan Africa.

Neural Networks in Action

Neural networks power numerous agricultural innovations:

- **Disease Detection Systems:** The PlantVillage Nuru app utilizes artificial intelligence to diagnose crop diseases from smartphone images. Studies have shown that Nuru's accuracy in diagnosing cassava diseases is higher than that of agricultural extension agents and farmers.
- **Weed Identification Tools:** AI-driven weed detection systems, such as those developed by Precision AI, use machine learning and computer vision to identify weeds and enable precision herbicide application. These systems can significantly reduce herbicide usage and improve weed control efficiency.
- **Fruit Ripeness Assessment Systems:** Researchers have developed AI models that determine the ripeness of fruits like tomatoes by analyzing hyperspectral images, allowing farmers to optimize harvest timing and improve product quality.
- **Livestock Monitoring:** AI-enhanced monitoring frameworks have been developed to assist in evaluating and maintaining animal welfare by analyzing video streams to identify individual animals and specific behaviors that can indicate health issues.
- **Soil Analysis Tools:** AI-enabled soil pH classification systems use colorimetric paper sensors and smartphone cameras to classify soil properties, providing farmers with quick and cost-effective soil analysis.

NLP is the branch of AI concerned with the interaction between computers and human language. NLP enables machines to understand, interpret, and generate human language, powering technologies like voice assistants, language translation services, and text analysis tools. For example, NLP algorithms can analyze social media posts to gauge public sentiment about agricultural policies or interpret scientific papers to extract relevant information for researchers. In agriculture, NLP techniques can allow farmers to interact with AI systems using natural language, letting them ask questions or provide instructions related to farming activities. NLP can also be applied to analyze social media posts, news articles, market reports, and other text data to extract insights about consumer food preferences, emerging trends, or potential supply chain disruptions.

Transformers are a type of neural network architecture that revolutionized the field of NLP by introducing the attention mechanism. Traditional neural networks process sequential data (like text or speech) in a strict order, making it difficult to capture long-range dependencies. The attention mechanism in Transformers allows the model to selectively focus on different parts of the input sequence when processing each element, enabling better modelling of long-range dependencies and context. Transformers were initially developed for machine translation

tasks but quickly became state-of-the-art for many NLP tasks, such as text summarization, question-answering, and language modeling. Their success led to the development of large language models like GPT, BERT, and, more recently, models like GPT-3 and ChatGPT.

LLM is an artificial intelligence system trained on vast amounts of text data to understand and generate human-like language. Specifically, an LLM is a neural network model with many parameters (often billions or even trillions) that is trained on a massive corpus of text from the internet, books, articles, and other sources. During this training process, the model learns patterns and relationships in the data, allowing it to understand and generate fluent text that resembles human language. LLMs underpin many of the latest AI language models and conversational assistants like GPT-3, PaLM, ChatGPT, BLOOM, and LaMDA. The large training allows these systems to capture comprehensive language understanding to engage in open-ended dialogue.

Computer Vision focuses on how machines can gain high-level understanding from digital images or videos. This field combines image processing techniques with deep learning, enabling machines to “see” and interpret visual information. In practice, computer vision can be used to monitor crop health by analyzing drone imagery or to sort produce based on quality and ripeness.

Appendix 2. The Enabling Role of Digital Public Infrastructure

AI cannot deliver value at scale without a robust underlying digital infrastructure. AI has the potential to become a transformative force in smallholder-dominated agricultural ecosystems. From precision farming and personalized advisories to predictive analytics for credit and insurance, AI offers the promise of making farming more efficient, more resilient, and more inclusive. However, while these possibilities are exciting, a critical question often goes unasked: What does it take for AI to actually work at scale for real farmers in LMICs? The answer lies beneath the surface in systems that are increasingly recognized as essential elements in the process of delivering government services to citizens: **Digital Public Infrastructure (DPI)**. Just as roads, power, and irrigation enabled the last agricultural revolution, today's leap forward depends on DPIs: foundational systems like digital identity, digital payments, and data exchange frameworks. These DPIs enable governments and the private sector to deliver essential services to citizens, promote economic growth, and drive social inclusion. Different DPIs can be bundled together to create sectoral transformation. For instance, DPI use-cases like digital identity, verifiable credentials, and citizen bank account mapping can work in tandem to create a system of direct benefits transfer, as seen in countries such as India.

Significant progress has been made in LMICs around the world in building foundational DPIs. Today, many governments are also investing in building agriculture-specific DPIs such as farmer identity registries, land records, open service networks, and data exchange frameworks. The most sophisticated algorithms are only as good as the data they are fed; the most personalized advisories are meaningless if they cannot reach the right farmer, at the right time, and in a trusted and accessible way. DPI enables all of this: it connects fragmented systems, reduces friction, and allows AI to function in a grounded, inclusive, and scalable manner. This report has already covered many of the ways that AI can be applied in agriculture, including delivering precision farm advisories, improving access to credit and insurance, forecasting prices, and optimizing input usage. The real question, however, is no longer what AI can do, but what it needs to be able to work for farmers, especially in ways that are cost-effective and scalable. AI systems depend on a few core conditions to be effective:

- Access to clean and contextual data;
- Ability to identify and reach the right users;
- Secure and consent-based data sharing;
- Way to deliver services at the last mile, the final stage where services actually reach farmers and rural communities.

In agriculture, these conditions are rarely met on their own. This is where DPI plays a critical and enabling role.

The DPI approach is essential for making AI work in agriculture for four reasons:

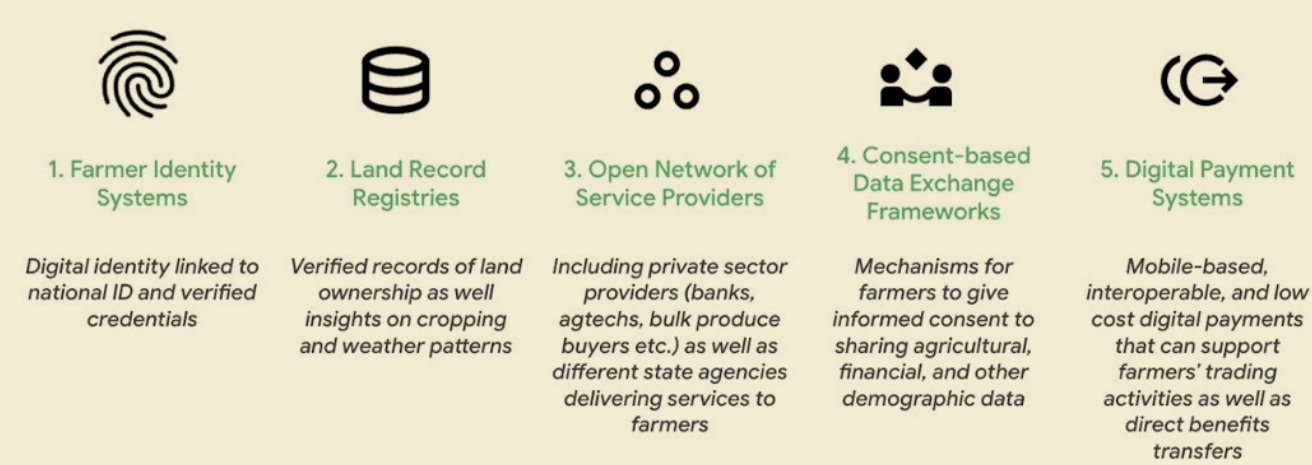
1. Contextualizing agricultural systems: AI models need trustworthy data to generate useful outputs. In the agricultural context, data are often siloed, inconsistent, or unavailable in usable formats. Through investing in agricultural DPIs that provide structured and verified data stacks for weather, soil health, crop history, and market trends, the state and private sector can create a solid foundation on which AI can build.

2. Linking data to farmers and their land: Personalization is only possible if an AI-based system knows who the farmers are and where they are farming. Digital identity, verified credentials, and authenticated land records are critical components of agricultural DPI that allow this connection to be made. Without them, any AI-generated recommendation risks being generic and ineffective.

3. Enabling secure and consent-based data sharing: As AI systems begin to draw on multiple data sources—such as government records, transaction histories and sensor data—it becomes vital to ensure that data are shared in a way that respects privacy and provides guardrails against any misuse of data. Agriculture-specific data exchange platforms, such as the Unified Lending Interface (ULI) created by India's central bank, are a mechanism for farmers to share their data securely, with clear consent, and appropriate levels of abstraction through tokenization to prevent any unintended consequences of data sharing.

4. Delivering services at scale: AI creates value if its insights reach farmers in the context of advisory and extension services when they need them. DPI enables this kind of delivery through open networks of agricultural service providers, where multiple actors—including advisory providers, financial institutions, and input sellers—can plug into the same infrastructure and serve farmers more effectively. The power of open networks is that they create interoperability. Once providers have done the work to be compliant with the DPI called Beckn Protocol that underlies most open networks, they can be discovered and programmatically composed into multiple different farmer-facing applications without requiring extensive technology and business integration. The report has looked at multiple examples of agricultural DPIs. Five agricultural DPIs can be considered to be foundational to enabling AI in agriculture (figure 3.1):

Figure A.2.1. Five foundational agricultural DPIs



Google Cloud India (2025)

The significance of DPI does not stop at agriculture. Farmers are not only cultivators: they interact with many different layers of the public and private welfare ecosystem. Across India and other countries, a wide range of government schemes, entitlements, and benefits is available to rural citizens. However, many of these go untapped due to fragmented systems and limited awareness farmers. Adopting a DPI-first approach creates the possibility of AI systems that do more than just deliver highly personalized farming advice; these systems can also help discover and route eligible services such as welfare schemes, nutrition programs, educational subsidies, and health benefits (box 3.1). Through the DPI approach, we imagine a future where agentic AI can tap into this underlying digital infrastructure to enable modular and citizen-centric service delivery, where the same infrastructure can respond to a person not simply as a farmer but more broadly as a parent, a pensioner, a jobseeker, or a student. In this model, AI becomes a tool for smarter farming with a layer of intelligence on top of inclusive public infrastructure that is capable of making the state more responsive, efficient, and human-centered. This is the real promise of aligning AI with DPI: not only scale, but also equity and integration in how services reach the last mile.

A working model and emergent blueprint from Uttar Pradesh in India

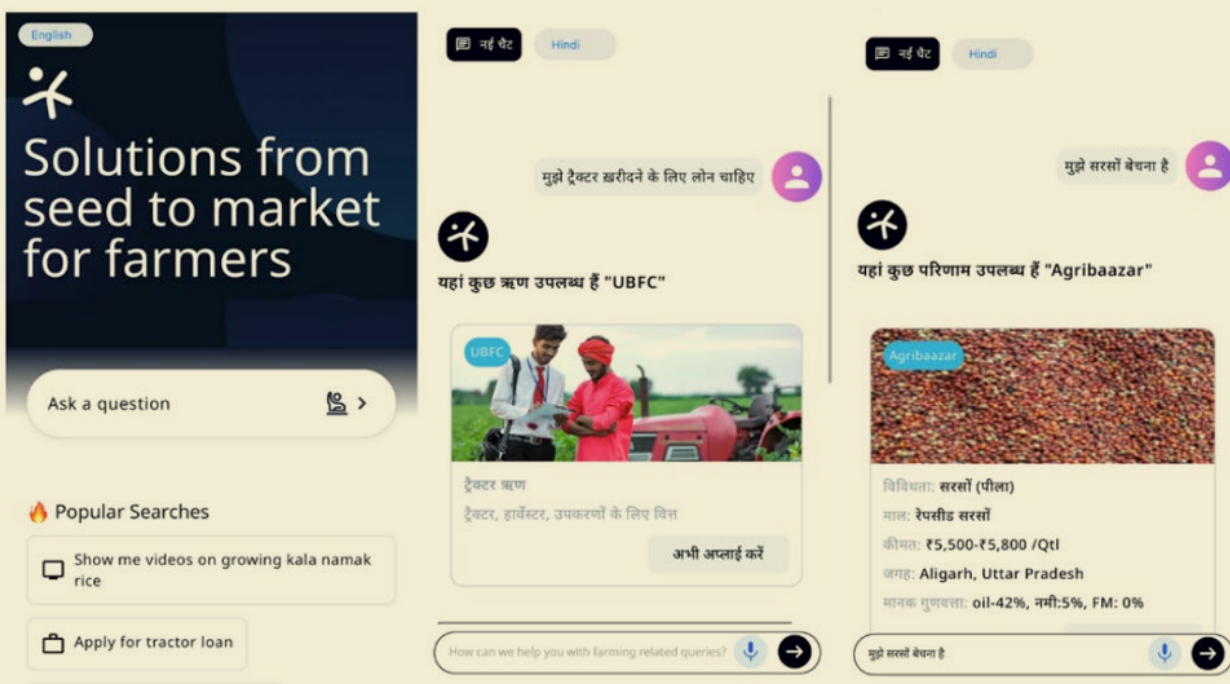
What has been described thus far in this chapter is more than a theory; it is very much informed by technology infrastructure that Google Cloud, International Finance

Corporation, and the World Bank are building in the Indian state of Uttar Pradesh.

These institutions have deployed an Open Network for Agriculture, which taps into the state's revenue department records of farmer land ownership. It then combines these data with India's national identity system, Aadhaar, to verify farmer data and use a backend-enabled open network for agriculture through which the intents and needs of farmers can be broadcast to agricultural service providers and the providers' catalogs of offerings can be shared with farmers (figure 3.3).

This entire service is being accessed by farmers through a conversational interface powered by a Gemini agentic framework that can be used in multiple different farmer applications. The network was announced by the Uttar Pradesh government on January 7, 2025, and initial transactions kick-started in the week of March 17, 2025 (figure 3.2). Early analysis showing that more than 1,000 farmers have been reached with three use-cases of farm advisories, market linkages and loans; early impact assessment has shown that farmers who are selling produce to the Uttar Pradesh Open Network for Agriculture are seeing a 10-15 percent uptick in their profits⁹⁰ that results from costs savings related to transportation, labor, and reduced penalties for wastage and bag weight.

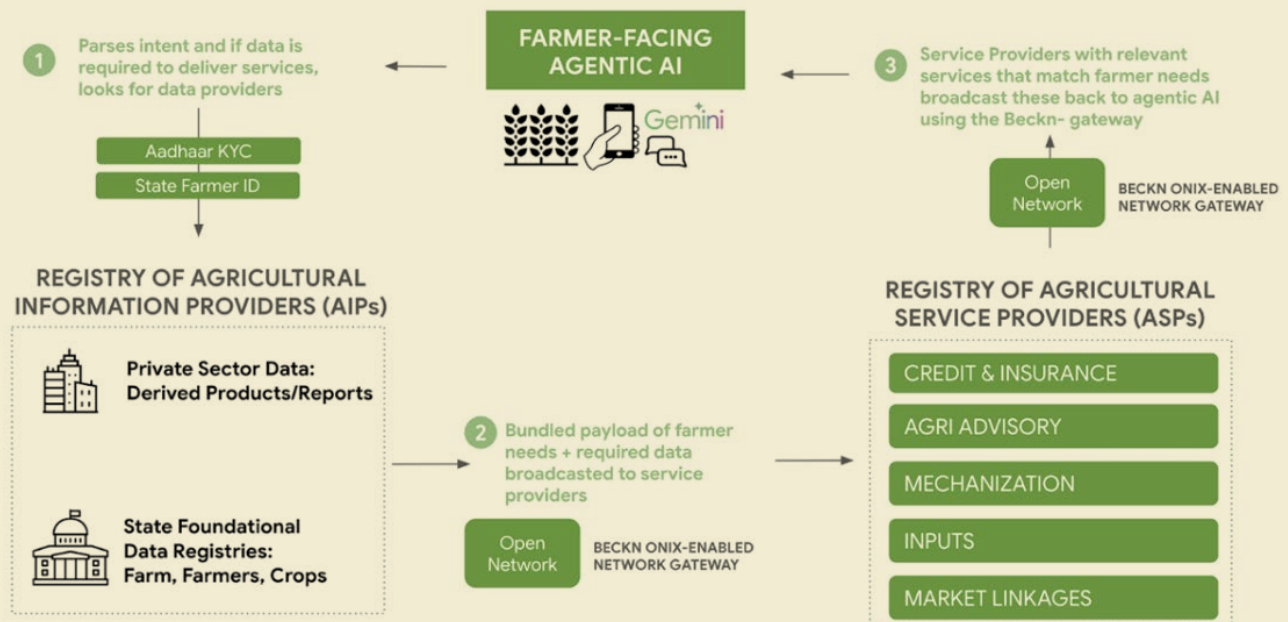
Figure A.2.2. Screenshot from the deployed web application from Uttar Pradesh. The second and third are in Hindi, demonstrating vernacular capabilities. The second screenshot shows a farmer querying for a tractor loan, and the third shows a farmer looking for opportunities to sell produce



Google Cloud India (2025)

⁹⁰ Based on primary research conducted by IFC team in March 2025

Figure A 2.3. Technical Design of Agentic AI deployed in Uttar Pradesh, India



Google Cloud India (2025)

The promise of aligning investments made in AI for agriculture with DPI is clear: smarter, more personalized, and more inclusive service delivery in agriculture. This promise, however, only translates into reality if certain conditions are met. These conditions cover technology and extend to the institutions, regulations, and physical infrastructure that surround it. Building an AI-powered agricultural ecosystem on top of DPI is not only a design challenge; it is an execution challenge that will require careful attention to both enablers and bottlenecks. Several systemic enablers must be in place for this vision to work.

- First, DPI needs long-term institutional stewardship. These are not one-off information technology projects; rather, the state needs to view them as an asset like a bridge or a highway that it owns and needs to constantly maintain and improve in the public interest.
- Second, local capacity-building is key. Extension workers, agri-entrepreneurs, and service providers need to be equipped to navigate this new system and support farmers in doing the same.
- Third, data foundations must be reimagined from the ground up. As more and more governments adopt the DPI approach, it is expected that they will soon realize that foundational registries are incomplete, unreliable, or being created for the first time. Land records, farmer identity systems, and verified service provider directories are essential elements of DPI, but building or cleaning them is a long and complex process that often requires coordination across departments, legal and regulatory changes, and significant fieldwork. This transition will require patient investment in state capacity and governance reforms.

Grounding Digital Innovation in Rural Realities

When these challenges are resolved, it will be essential to address another key lesson that has long been clear to development sector practitioners: technology does not deliver meaningful outcomes in isolation. The effectiveness of an AI-led and DPI-based approach hinges on its connection to physical infrastructure and field realities. For instance, in Uttar Pradesh, a Beckn-enabled open network is allowing bulk purchasers to make digital procurement offers for crops like mustard and wheat. Farmers can use Gemini to discover and express interest in these trades through a conversational interface. The system increases market visibility for farmers and unlocks new trade possibilities. In practice, however, farmers can only truly benefit from these offers if the farmers themselves are matched to hyperlocal collection centers, processing units, and procurement hubs. Otherwise, the burden of transporting goods to distant marketplaces or buyers cancels out the gains from digital discovery. The insight is simple but critical: DPI and AI must be grounded in the logistical and geographic realities of rural life.

Designing for Inclusion from the Start

Finally, inclusivity must be built into the design from day one. Women farmers, tenant farmers, and other marginalized communities are often the least visible in existing data systems and the most at risk of being left out. A DPI-driven approach creates the opportunity to correct this by ensuring they are proactively included in registries, in eligibility criteria, and in the outreach strategies that accompany new services.

Technology is Just the Beginning

As demonstrated in the pilot in Uttar Pradesh, the technology itself can now be deployed within days, thanks to Google's DPI-in-a-Box offering. However, the bulk of the ongoing work lies in institution-building. This requires long-term vision, operational patience, and a willingness to coordinate across silos.

The potential of AI in agriculture is real—but its success depends on the infrastructure built beneath it: digital and physical, institutional and social. The challenge ahead is not simply to design smart systems but to ensure that they reach rural communities and deliver value to the people who need them most.

Despite the presence of enablers and promising use cases, significant barriers still constrain the widespread adoption of AI in agriculture. The following section explores these limitations, including structural, financial, ethical, and environmental concerns.

Selected Case Studies



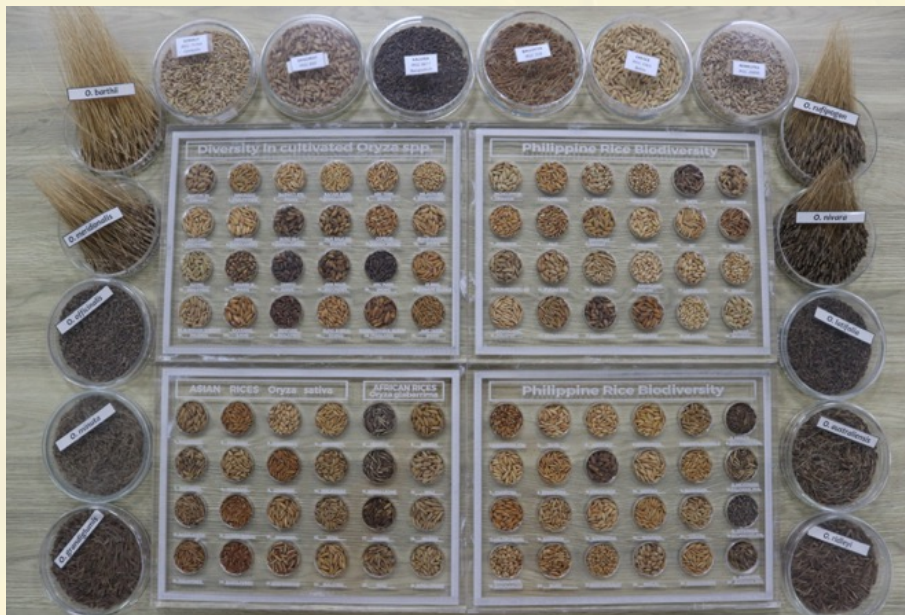
Case Study 1. AI-Driven Transformation in Genebank Utilization by IRRI

IRRI is pioneering a transformative approach to genebank management by integrating cutting-edge AI technologies. This initiative, funded by Google.org's AI for Social Good program, aims to tackle critical global challenges, such as climate change and food security by revolutionizing the way genebank resources are utilized.

Challenges with Traditional Methods

Plant genetic resources are the cornerstone of food security and environmental sustainability. Genebanks have long been essential for conserving these resources, but their potential is underutilized globally. For example, only about 5 percent of the 132,000 rice samples (figure B4.3.1) conserved at IRRI's genebank (IRG) have been actively used by IRRI's breeding programs. It is crucial to accelerate the use of genebank resources to effectively respond to climate change challenges.

Figure B1.1. Diversity of rice germplasm



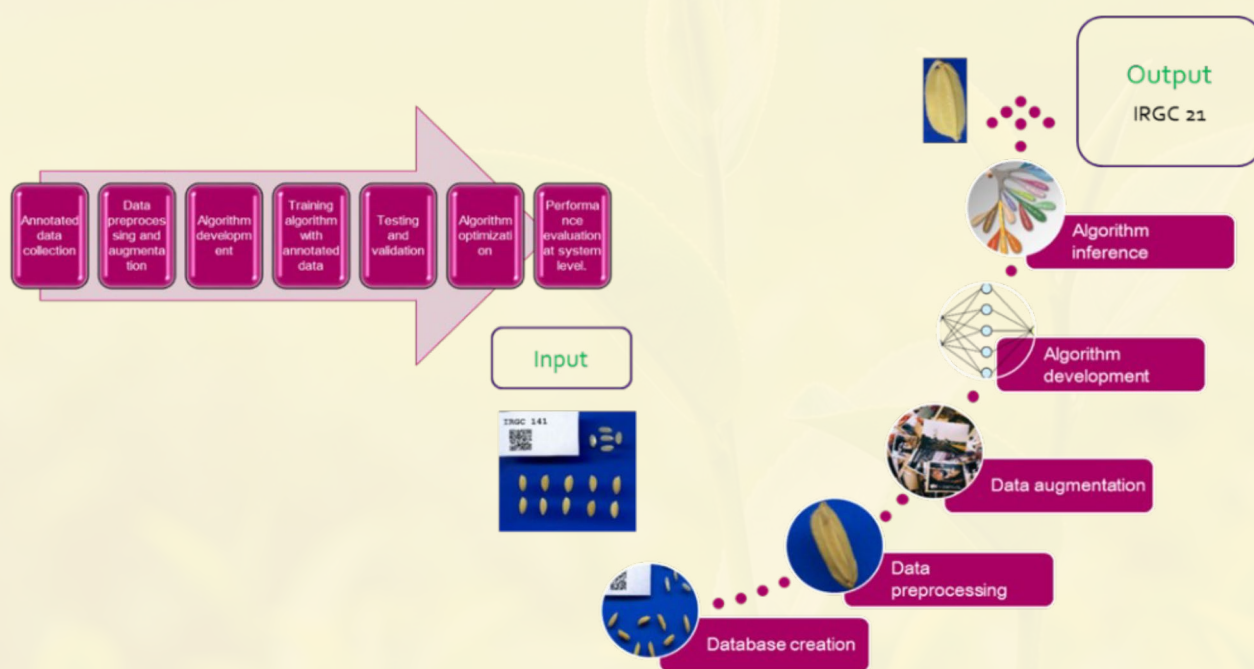
Source: International Rice Research Institute (IRRI)

Although genebanks are vital for preserving genetic diversity, they also play a crucial role in enhancing the use of germplasm by generating valuable information about the conserved materials. However, traditional methods of germplasm evaluation are slow, tedious, and expensive.

AI-Powered Solutions: IRRI's Innovation

To overcome these limitations, IRRI has developed an AI-driven system that dramatically accelerates the screening process for rice samples, particularly focusing on traits related to climate resilience. The innovation lies in integrating AI with advanced phenotyping techniques. The AI system, trained on a vast dataset of seed images, enables the accurate identification of germplasm accessions (varieties) based on seed images. This system also extracts features from seed images, which helps in grouping and classifying the germplasm within the genebank collection. This information allows for the creation of pooled samples from bulked accessions, which then can be evaluated using high-throughput methodologies to identify useful traits (figure B4.3.2). Benchmarking against well-established checks is key to ensuring the accuracy of these identifications.

Figure B1.2. Machine Learning model for rice seed identification



Source: International Rice Research Institute (IRRI)

This methodology allows researchers to quickly assess the performance of a large number of varieties for specific traits. The AI system accelerates the identification of resilient varieties and significantly reduces the costs associated with traditional screening methods.

Project Results

Although still in the first year of this pilot project, there has been significant progress. The AI model has been trained on half of the IRG collection, resulting in the formation of approximately 7,000 pooled samples (figure B4.3.3). These samples have been screened for tolerance to two key climate resilience traits—drought and flooding—within a single season.

Figure B1.3. Seed samples ready for seeding



Source: International Rice Research Institute (IRRI)

This approach has enabled the screening of around 60,000 accessions for two stresses in only one season (figures B4.3.4 and B4.3.5), identifying valuable accessions. Although more time is needed to confirm the results and accurately establish the identity of these accessions, this is a remarkable achievement. Before this project, only about 20,000 samples had been screened for flood tolerance since the genebank opened in 1971.⁹¹

⁹¹ CGIAR (2019), <https://genebanks.cgiar.org/wp-content/uploads/2020/04/Impact-Brief-1-Villanueva.pdf>

Figure B1.4. Screening the pooled samples for flood tolerance



Source: International Rice Research Institute (IRRI)

Once the AI model is fully trained on the entire collection, it will be possible to evaluate and confirm results for the entire collection in about two years. In contrast, screening the entire collection using traditional methods would take a decade. This method accelerates the process and reduces costs dramatically; estimates suggest that it could be done for about one-sixth of the cost of traditional approaches.

Figure B1.5. Screening the pooled samples for drought tolerance



Source: International Rice Research Institute (IRRI)

The cost-effectiveness of this approach ensures comprehensive screening of IRRI's entire rice collection, making valuable genetic resources available to researchers who can use them to develop new climate-resilient varieties. The project's economic implications are equally impressive, with projected returns of US\$30.79 billion over five years, driven by the adoption of these improved varieties.

Scalability and Future Prospects

IRRI's AI-powered genebank screening system is designed with scalability in mind. The methodologies developed can be adapted for several other traits in rice, as well as for other crops and regions, offering a global template for genebank utilization. As other genebanks adopt similar technologies, the potential for increased utilization of plant genetic resources is immense, contributing significantly to the achievement of the United Nations SDGs.

The project also lays the foundation for developing a digital ecosystem that meets the diverse needs of genebank users. By providing detailed genomic and trait information, policy guidelines, and environmental data, this ecosystem will empower breeders and farmers to make more informed decisions, further enhancing the impact of genebank resources.

Conclusion

The AI-driven transformation of genebank utilization at IRRI represents a significant leap forward in leveraging technology to address global agricultural challenges. By unlocking the full potential of genebank resources, this initiative is poised to make a lasting impact on global food security and climate resilience. As the technology is scaled and adopted by other genebanks, its benefits will extend far beyond rice fields, contributing to a more sustainable and resilient global food system.

Case Study 2. AI-powered location-specific, season-smart, and tailored decision support system transforming food production in SSA

Introduction

Over 65 percent of the population of Africa relies on subsistence farming, and more than 35 percent of the population lives on less than 1.25 dollars a day.⁹² Most farmers own less than one hectare of land, far below the “viable farm size” required for sustainable living.⁹³ Smallholder farm plots are fragmented, scattered, and of poor quality. Mechanization levels are less than 30 tractors per km² compared to over 240 in other regions.⁹⁴ On average, fertilizer consumption is 20 kg per hectare, compared to a global average of about 135 kg per hectare.⁹⁵ Some countries in the region have increased investment in importing fertilizers, but there has not been a significant increase in crop yield increases. This finding is likely due to the blanket application of inputs regardless of differences in soils and crop types and landscape and farming systems. Because of these and other reasons, the yield gap in the region can reach up to 80 percent, offering the potential for most farmers to triple or quadruple their production.⁹⁶

NextGen Agro-advisory Decision Support Tool (DST)

To address these complex challenges, the recent advances in AI, machine learning (ML) and advanced data-analytics presented opportunities to design bundled solutions tailored to specific environmental, household, socio-economic and climatic conditions. An exemplary work related to this is the development of an integrated DST known as NextGen agroadvisory,⁹⁷ developed by a community of national partners called the Coalition of the Willing (CoW).⁹⁸ ⁹⁹ The advisory recommends the appropriate type and amount of organic and inorganic fertilizers based on specific fields, households, and climate conditions. The DST uses recent advancements in data collection, storage, and analytics; the workflow is organized into four modules: data, analytics, dissemination/advisory delivery, and feedback modules (figure B4.6.1). It is developed, validated, and piloted for wheat while being validated for other crops in Ethiopia.

From data to tailored advisory

Data drive the engine for developing advisories for informed decision-making. Agricultural data,

92 Statista (2025), <https://www.statista.com/statistics/293144/people-in-extreme-poverty/>

93 Giller, et al. (2021), <https://link.springer.com/article/10.1007/s12571-021-01209-0>

94 Gitau, et al. (2020), https://www.researchgate.net/publication/344499545_AGRICULTURAL_MECHANIZATION_STATUS_IN_AFRICA_AN_OVERVIEW

95 APNI (2023), <https://growingafrica.pub/wp-content/uploads/2023/08/GA-1-23-low.pdf>

96 <https://tabledebates.org/podcast/episode48#:~:text=The%20yield%20gap%20refers%20to,or%20even%20quadruple%20their%20harvests.>

97 <https://nextgenagroadvisory.com/>

98 CoW (2023), <http://ethioagridata.com/>

99 Desta, et al. (2021), <https://cgispace.cgiar.org/items/333f228d-f017-4a06-bd92-bf4912fd0a39>

especially site-specific agronomic inputs and associated attributes, are costly to obtain and usually limit the development of DST in the sector. The challenge is both quantity and quality. To this end, the CoW developed a crowdsourcing approach where members (both individuals and institutions) collected, standardized, and harmonized tens of thousands of datasets on crop responses to organic and inorganic fertilizers, agricultural lime and associated crop management options.¹⁰⁰ Guidelines and directives were developed to facilitate data access and sharing.¹⁰¹ Once a critical mass of crop management data is obtained, an automatic ETL (extraction, transformation, and loading) workflow¹⁰² is developed to combine these data with key environmental variables (covariates) to create a “big data” set for the ML engine to leverage.

As part of the data collection, the team is also building localized corpora of text from agronomic literature, expert knowledge, extension agents, and other localized agricultural information, complementing and updating the ML engine with localized recommendations from the LLM. Using the various datasets made available through the above step, an integrated DST is developed using data mining and machine learning algorithms¹⁰³ to guide extension workers and farmers on the following:

- Which types (combinations) of inputs (such as fertilizer, organic material, lime, ISFM, and climate-smart agriculture (CSA))
- In what amounts
- At what time of the season
- For which plots or farms should they be applied.

The analytics module contains a chain of components. A data-driven ML approach is used to develop yield-to-nutrient and other management measures response surface and extract advisory for sites determined by the scale of analysis.¹⁰⁴ ¹⁰⁵ Process-based models—such as the QUantitative Evaluation of the Fertility of Tropical Soils (QUEFTS) and the Decision Support System for Agroecology Transfer (DSSAT)—are integrated to predict water-limited yield and provide a wider window in the optimization space and provide various good agronomic practices (GAPs), such as optimal planting date, optimal varieties, and time of input application. The climate information forecast/service and the DSSAT models are integrated into the Ethiopian Digital AgroClimate Advisory Platform.¹⁰⁶

100 EIAR (2025), <https://datahub.eiar.gov.et/dataverse/cn>

101 CoW (2020), http://www.ethioagridata.com/Resources/COALITION_OF_THE_WILLING_-_DATA_SHARING_GUIDELINES.pdf

102 CIAT (2025), <https://github.com/orgs/CIAT-DAPA/teams/eth-fertilize/repositories>

103 Abera, et al. (2022), <https://www.cambridge.org/core/journals/experimental-agriculture/article/datamining-approach-for-developing-sitespecific-fertilizer-response-functions-across-the-wheatgrowing-environments-in-ethiopia/2CC4400FF8239FC24373ACBE8CA9071F>

104 Abera, et al. (2022), <https://www.cambridge.org/core/services/aop-cambridge-core/content/view/2CC4400FF8239FC24373ACBE8CA9071F/S0014479722000047a.pdf/div-class-title-a-data-mining-approach-for-developing-site-specific-fertilizer-response-functions-across-the-wheat-growing-environments-in-ethiopia-div.pdf>

105 Feyera, et al. (2024), <https://www.sciencedirect.com/science/article/abs/pii/S0378429024001667>

106 EDACaP (2020), <https://ethioagroclimate.net/>

Performance and scalability on smallholder farmers' fields

Validation of the advisory, conducted by Digital Green and District Bureaus of Agriculture, using 277 farmers across various agroecologies in 2021, showed a 25 percent increase in wheat yield and US\$580 per hectare per season increase in profit compared to blanket recommendations.¹⁰⁷ The DST is also around 30 percent more efficient in terms of nitrogen and water use than blanket recommendations. Comparing the wheat grain yield of farmers who used the advisory and those who did not, the results show that the former have gained a yield advantage of up to 38 percent.¹⁰⁸ Encouraged by these achievements, the advisory was disseminated to over 60,000 farmers during the 2022 and 2023 seasons.^{109 110 111}

Listening to the users

The DST's feedback module gathers input from extension workers, farmers, and other users about the content, dissemination methods, and other advisory aspects. It also collects specific information about farmers' needs, challenges, priorities, and goals, and their recent, current, and future management practices. This information is then used to refine the data, model, and dissemination modules for adaptive learning. This process makes the DST more agile and human-centered by capturing the local constraints and ambitions of individuals and groups of farmers.

Conclusion

The NextGen agroadvisory DST has done the following:

- Demonstrated the journey of data collection, standardization, and transformation to actionable insights,
- Highlighted the power of data in creating tools that empower farmers to make informed decisions,
- Unveiled practical applications of data-driven and process-based solutions that contribute directly to agronomic gains,
- Demonstrated the power of data and improved analytics to unlock agricultural productivity and empower farmers in the Global South.

The approach is poised to contribute to sustainable soil health management and reshape fertilizer-focused initiatives in alignment with the African Union's agrarian goals (Figure B2.1.).

107 Urrea-Benitez (2024), <https://alliancebioversityciat.org/stories/smarter-fertilizer-ai-powered-recommendations-boost-wheat-yields-ethiopia>

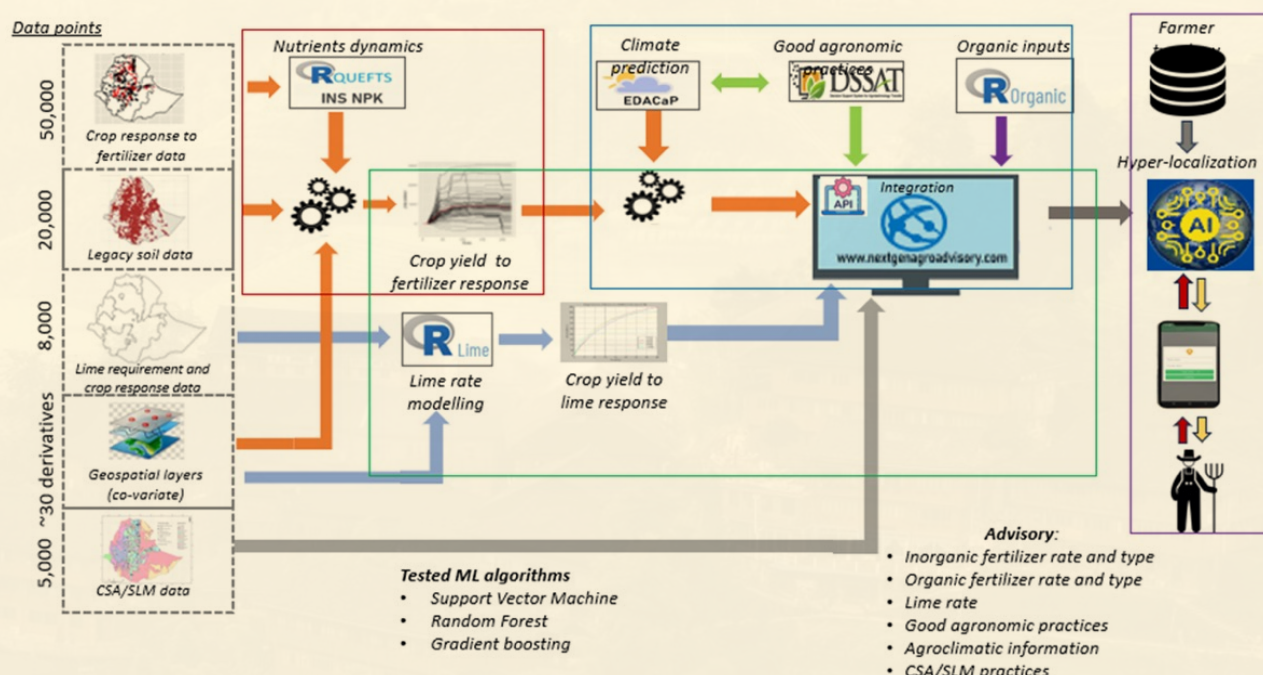
108 Liben, et al. (2023), <https://cgspace.cgiar.org/items/e5a0700f-588d-4b15-a1f3-f840549c82c7>

109 Ebrahim, et al. (2023), <https://cgspace.cgiar.org/items/c8db5c81-e23e-4327-a7b2-b414e36fa530>

110 Elshaday, et al. (2023), https://digitalgreen.org/wp-content/uploads/2023/12/Telegram-Bot-Assisted-SSFR-Assessment-Report_-Digital-Green-and-Alliance-of-Biodiversity-and-CIAT-1.pdf

111 https://lookerstudio.google.com/u/0/reporting/010707fb-fc8c-4dd8-8960-e7f44d4818a2/page/p_qq4vz3c26c

Figure B2.1. Workflow of the NextGen Fertilizer Advisory Component



Source: CGIAR (2022)

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Case Study 3. From Data to Action: Transforming Land Restoration with LDSF and AI

The Land Degradation Surveillance Framework (LDSF), an innovative initiative developed by CIFOR-ICRAF that represents a transformative application of AI in monitoring and addressing land degradation¹¹². This methodology provides a systematic and robust approach to assessing soil and ecosystem health across diverse landscapes, which is a pressing need given the global challenges posed by land degradation and its impact on food security, biodiversity, and climate resilience.

The global challenge of land degradation is exacerbated by the lack of consistent and reliable information on its status and trends over time. Current limitations in data collection and analysis create significant obstacles to understanding the scale and dynamics of degradation. Without robust evidence, land restoration risks being misinformed, leading to wasted resources and ineffective interventions. Such constraints also limit the precision and scope of the insights generated.

The urgency to address these gaps is heightened by the accelerating impacts of climate change. Interactions between land degradation and climate-induced shocks pose a critical threat to the resilience of both social and ecological systems. A major challenge lies in the ability to assess these interactions comprehensively, which is crucial for designing targeted, adaptive strategies. Additionally, there is a pressing need for site-specific land management solutions that can address localized challenges while ensuring the effective tracking of restoration interventions to measure their long-term impact on ecosystems and livelihoods.

AI in Action: How LDSF Transforms Land Management

The LDSF directly addresses the complex challenge of land degradation by embedding AI at its core. This integration fundamentally redefines how land degradation is monitored, leveraging advanced machine learning algorithms to analyze diverse datasets, including field measurements and satellite imagery. By employing AI-driven methodologies, the LDSF provides high-resolution insights into soil and land health indicators, enabling stakeholders to make informed, evidence-based decisions.

At the heart of the LDSF is a robust and flexible indicator framework designed to capture multi-parametric data on soil health, vegetation dynamics, and land use. These indicators, grounded in social, economic, and biophysical perspectives, offer a comprehensive assessment of ecosystem health (figure B4.14.1). By coupling these metrics with systematic sampling designs

¹¹² Land Degradation Surveillance Framework, <https://ldsfcifor.org/>

and advanced analytics, the LDSF ensures that data collection is both precise and scalable. Continuous sampling and data integration further enhance its utility, allowing for real-time updates and dynamic insights that inform adaptive management strategies over time.

Figure B3.1. LDSF Indicators



Source: LDSF



AI plays a pivotal role in optimizing these processes by significantly increasing the accuracy and depth of insights derived from LDSF data. Remote sensing technologies, amplified by AI, enable near-real-time monitoring of landscape changes, providing actionable intelligence. This dynamic capability ensures that restoration interventions are timely, targeted, and tailored to the specific needs of diverse ecosystems and communities.

The scalability and adaptability of the LDSF has positioned it as a cornerstone in global efforts to combat land degradation. Its applications span baseline assessments, monitoring and evaluation, research, and capacity development, making it an invaluable tool for diverse stakeholders, including government agencies, NGOs, and researchers. By providing robust methods for collecting, analyzing, and reporting data on soil health, land degradation, and vegetation dynamics, the LDSF supports a comprehensive understanding of landscape health across a wide range of ecosystems and land uses.

The framework's impact is evident in its ability to deliver precise, actionable insights that have transformed land management practices across the globe. By generating detailed landscape maps, the LDSF has guided site-specific interventions, significantly reduced soil erosion and enhanced agricultural productivity. For example, in regions where the LDSF has been deployed, the use of data-informed soil health practices has resulted in measurable increases in crop yields, directly contributing to food security and improved livelihoods for local communities.

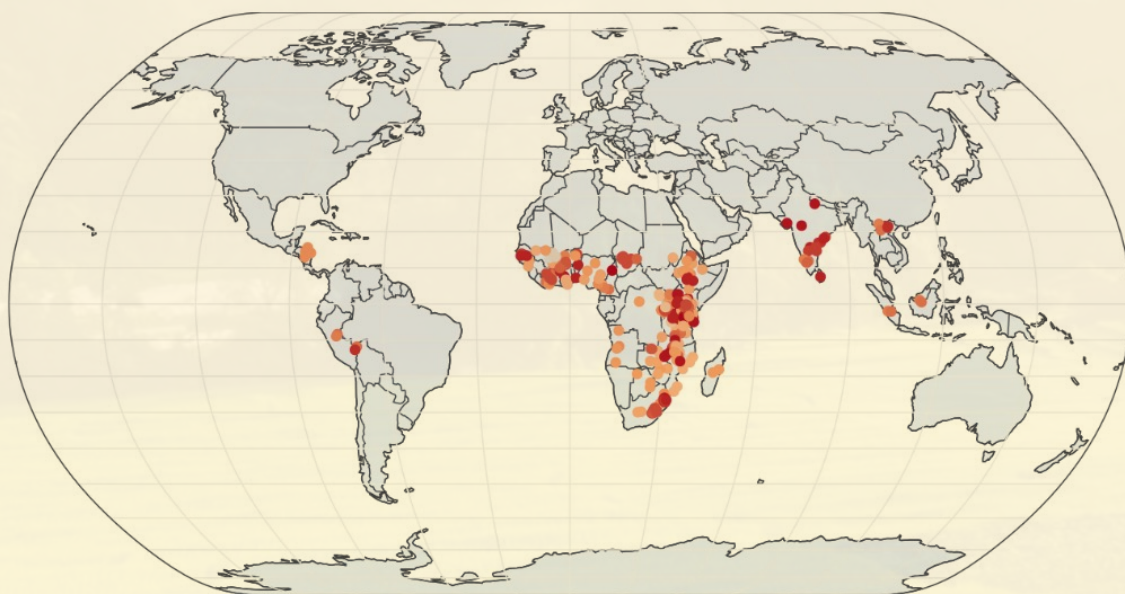
A key feature of the LDSF is its flexibility, which allows for the incorporation of diverse ecological indicators tailored to specific environmental and socioeconomic contexts. This adaptability ensures that the framework remains relevant across a wide array of landscapes from arid savannas to tropical forests. By utilizing a standardized yet customizable methodology, the LDSF guarantees consistency in data quality while accommodating the unique challenges and priorities of different regions. Such adaptability is not only critical for addressing complex environmental issues; it also fosters sustainable land management practices that are culturally and regionally appropriate.

Beyond its technical capabilities, the LDSF has proven to be a powerful platform for capacity development. Through hands-on training in data collection, analysis, and reporting, the framework empowers stakeholders to actively engage in monitoring and managing their landscapes. This participatory approach ensures that the knowledge generated by the LDSF is not only accessible but also actionable, enabling stakeholders to implement data-driven interventions effectively. The widespread adoption of the LDSF in more than 40 countries underscores its scalability and utility (figure B4.14.2). Its methodologies have been

successfully adapted to various ecosystems, demonstrating the framework's potential for broader application in addressing land degradation globally. As a flexible yet rigorous system, the LDSF continues to serve as a vital tool in the pursuit of sustainable land management, resilience building, and ecological restoration.

Figure B3.2. Map of LDSF sites*

Each point represents a 10x10km site where the LDSF has been implemented.



Source: LDSF

**The boundaries and names shown on this map do not imply official endorsement or acceptance by the World Bank Group or its partners.*

LDSF: A Technological Bridge to Sustainable Land Management

The LDSF exemplifies how technology can bridge the gap between environmental science and practical action. The integration of AI enhances the precision and efficiency of the framework, and it democratizes access to critical environmental data. By providing open-source tools and training modules, the LDSF empowers local stakeholders, including farmers, researchers, and policymakers, to engage actively in land management processes. This participatory approach ensures that the framework's benefits are widely distributed and that its recommendations are grounded in local knowledge and expertise. The LDSF holds immense potential as a global public good, poised to address the interconnected challenges of land degradation, food security, and climate resilience. By fostering collaborative investments in continuous monitoring and soil sampling, the LDSF can further enhance its capacity to provide high-resolution, near-real-time insights into land health. Such advancements would enable stakeholders to prioritize interventions more effectively and adapt strategies based on dynamic conditions.

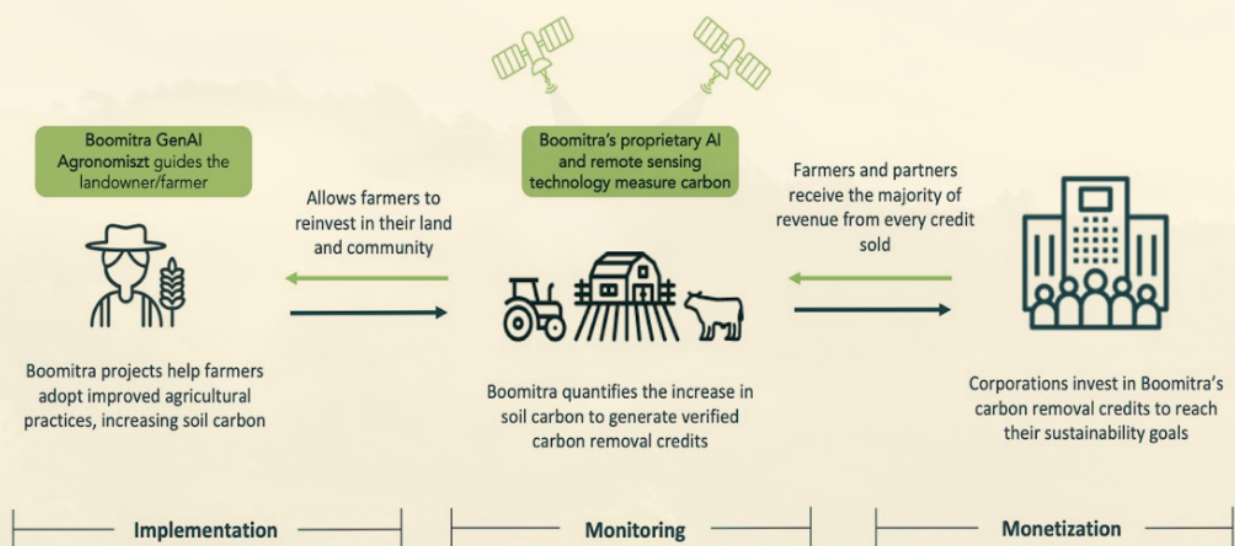
Expanding the use of the LDSF across regions and sectors would unlock its full potential as a scalable data infrastructure. By removing data silos and integrating multi-parametric data, the framework could serve as a unified platform for analyzing and reporting on land health indicators. Doing this would not only support better decision-making but also promote a culture of transparency and collaboration among governments, NGOs, researchers, and local communities. Furthermore, recognizing the LDSF as a shared resource would encourage investments in its technological evolution, including the integration of advanced AI capabilities for even greater precision and adaptability. The LDSF's emphasis on participatory processes also opens doors for deeper community engagement, ensuring that local knowledge is valued and incorporated into restoration efforts. This approach enhances the relevance of interventions and fosters resilience at the grassroots level by empowering communities to take ownership of sustainable land management practices.

In conclusion, the LDSF stands as a testament to the transformative power of integrating technology with scientific innovation. By providing a robust, scalable, and participatory approach to land degradation monitoring, the LDSF demonstrates how AI can bridge the gap between data generation and actionable insights. Its successes highlight the importance of investing in shared, inclusive data infrastructures that prioritize collaboration and long-term sustainability. As the LDSF continues to evolve, its potential to drive meaningful change becomes increasingly clear. By removing data silos, supporting continuous monitoring, and fostering a culture of community-driven action, the framework delivers tangible benefits for both livelihoods and ecosystems. In doing so, it offers a powerful model for addressing some of the most pressing global challenges, including land degradation, climate adaptation, and food security. Ultimately, the LDSF's integration of technology and participatory action ensures that its impact is not only measurable but also equitable, making it a vital tool for a sustainable future.

Case Study 4. Leveraging AI for Carbon Measurement

Boomitra, a soil carbon project developer, utilizes proprietary remote sensing and AI technology to measure soil organic carbon (SOC) sequestration globally. With a network of global partners, Boomitra supports farmers and ranchers across the Global South to adopt agricultural practices that sequester carbon. Boomitra then quantifies the additional carbon captured and works with international standards bodies to generate Verified Emission Removals (VERs), commonly called “carbon credits.” Farmers and ranchers earn most of the proceeds from each carbon credit sold (figure B4.1). By combining satellite data, AI, and an unparalleled database of georeferenced soil samples, Boomitra measures SOC at scale. Boomitra’s technology has been pre-validated by a UNFCCC third-party auditor. Continuous sampling and data integration further enhance its utility, allowing for real-time updates and dynamic insights that inform adaptive management strategies over time.

Figure B4.1. Boomitra GenAI



Source: Boomitra

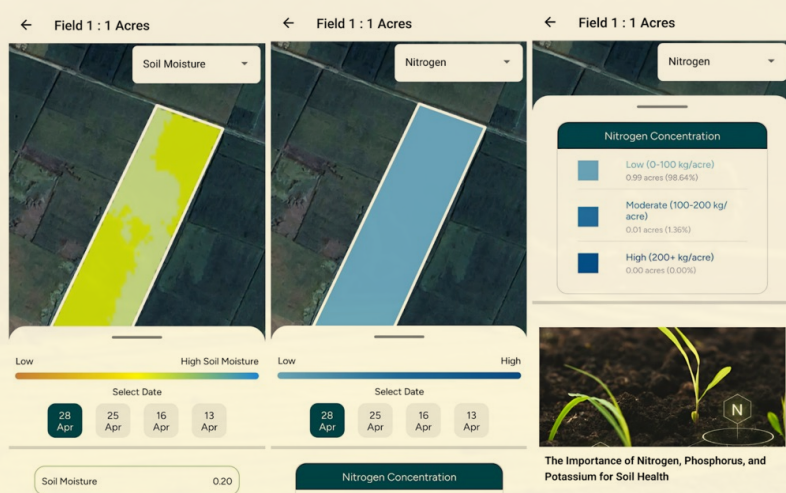
Traditional methods of measuring soil carbon—such as soil sampling and laboratory analysis—are labor-intensive. They require extensive fieldwork and expensive sample processing. Besides being time-consuming and costly, traditional measurements often need more spatial resolution and may not capture the full variability of soil carbon levels across landscapes. For example, physical samples from two points on a one-acre farm could yield different results. Consequently, there is a pressing need for more efficient, accurate, and scalable soil carbon measurement approaches. Boomitra leverages advanced satellite and AI technology to eliminate the need for extensive soil sampling for accurate soil carbon

measurement. This innovation has reduced soil carbon measurement costs by 90 percent. Boomitra's third-party, internationally certified technology is built upon an existing archive of more than 1 million soil samples collected by professionals and analyzed at nationally accredited soil laboratories. Boomitra fuses this ground-truth data with insights from dozens of satellites across the electromagnetic spectrum in a precise machine learning methodology that delivers accurate results to measure what is beneath the soil.

Boomitra's approach ensures proper generalization across various soil, climate, seasonal, and land use conditions. This robust process is used to build regional soil models across the globe with accuracy, detail, and scalability. Boomitra measures the absolute SOC (30 cm deep), soil moisture (1 m deep), and nutrients on a given plot of land. All insights are delivered with a 10 m resolution. This process is cost-effective, time-efficient, and scalable across various landholding sizes, making Boomitra a global leader with projects spanning more than 5 million acres; 100,000 growers; and four continents. The farmer-first partnership model ensures that carbon markets and climate finance drive returns for farmers and ranchers while combatting climate change. The Boomitra App delivers precision insights to farmers and ranchers to help them save costs and improve yields (figure B4.15.2). With the Boomitra App, growers worldwide can do the following:

- Evaluate nutrient deficiencies and make informed decisions on irrigation and fertilisation to optimise plant growth and yield potential.
- Manage crop planting schedules, irrigation, fertilization plans, pest control measures, harvesting, and more with timely alerts.
- Monitor carbon sequestration progress and manage payments. The app empowers farmers and ranchers to make data-driven decisions, enhancing productivity and contributing to global sustainability.

Figure B4.2. Boomitra App



Source: Boomitra

Regenerative agriculture effectively removes carbon from the atmosphere and stores it in the soil. Agricultural soils have the technical potential to sequester 3 to 5 billion tonnes of CO₂ each year (IPCC), roughly 10 percent of global annual emissions. Soil carbon removal credits have emerged as a crucial climate change mitigation strategy. By storing carbon in the soil, Boomitra farmers and ranchers are not just capturing CO₂ from the air; they are improving soil health. This improvement means better water infiltration, increased biodiversity, healthier crops, increased climate resilience, and food security. For growers, this improvement translates to higher yields, less need for expensive inputs, secure jobs, and new revenue streams. The collective investment in soil ensures that communities worldwide can adapt to climate change while mitigating it.

Boomitra works with farmers and ranchers across the Global South, spanning diverse landscapes from the Chihuahuan and Sonoran deserts in Mexico, to the Pampas grasslands across South America, to grasslands and croplands in East Africa and croplands in India. For example, in East Africa, Boomitra partners with the World Food Programme and the Farm to Market Alliance to help farmers adopt improved agricultural practices, including reduced tilling, mulching with crop residues, organic manure application, water management, and agroforestry activities. Boomitra's project development and measurement approach ensures additionally, durability, and co-benefits for diverse stakeholders. These stakeholders include corporations with extensive supply chains and governments moving towards net-zero emissions. The digital MRV platform ensures complete transparency among all stakeholders, including farmers, implementation partners, and buyers. The environmental, economic, and market impacts of Boomitra's technology underscore its potential to drive significant positive change in the fight against climate change.



Source: Boomitra

Rose Khatambi Meja, a Boomitra carbon farmer on 3 acres in Kenya says:

"Since adopting improved agricultural practices, my harvest has gone from 8.9 kg to 18 kg per acre in 2 harvest seasons. I am confident that my yields will continue to improve with continued practice of these methods. These practices mitigate carbon emissions, reduce production costs, improve soil health, increase water retention, and boost production."

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