The use of artificial intelligence in food and agriculture systems

The state of Art

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About the Research Commissioning Centre

The Foreign, Commonwealth and Development Office (FCDO) Research Commissioning Centre (RCC) has been established to commission and manage research to enhance development and foreign policy impact. Led by the International Initiative for Impact Evaluation (3ie), the University of Birmingham, and an unmatched consortium of UK and global research partners, the RCC aims to commission different types of high-quality research in FCDO's key priority areas.

About the report

This report the use of artificial intelligence in food and agriculture systems: The state of Art focuses on examining the current state, potential, and challenges of artificial intelligence (AI) adoption in agriculture, with particular emphasis on low- and middle-income countries (L&MICs). It explores AI's applications across the agricultural value chain ranging from crop production and pest detection to predictive analytics and climate-smart solutions while assessing its effectiveness, ethical considerations, and equity implications. Drawing on narrative reviews, case studies, deep dives, and stakeholder engagements, the study identifies evidence gaps, infrastructure limitations, and governance challenges that hinder widespread and equitable adoption. Findings from this will inform policymakers, researchers, and development practitioners in designing inclusive, evidence-based, and context-specific strategies to scale AI in agriculture, ensuring benefits for smallholder farmers and promoting sustainable, equitable agri-food systems.

Review process

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Executive summary

Background and context

The use of artificial intelligence (AI) and automation promises to raise productivity, improve product quality, increase resource-use efficiency, alleviate labour shortages, promote decent employment, and enhance environmental sustainability (FAO 2022c). At the same time, the introduction of incompatible technologies can lead to limited adoption, exacerbation of inequities, and negative consequences for marginalised groups. This research suggests significant challenges to adopting these technologies, especially in low-resource settings. Researchers identified the incompatibility of AI-enabled solutions with digital skills and infrastructure as a key reason for ineffectiveness.[9] Findings from the study underscore the need for a robust digital infrastructure across low- and middle-income countries (L&MICs), and the need to prioritise digital literacy and relevant capacity building amongst the end users.

Findings and recommendations

This study revealed a growing interest in employing AI-enabled solutions in agriculture. Machine learning emerged as the most prominent intervention, while other notable approaches included automation and robotics, deep learning, neural networks, and predictive AI. AI-enabled solutions most commonly supported pest and disease detection in agriculture. Further research, including evidence gap maps and systematic reviews, to deepen these findings.

Study objectives and approach

The objective of this study was to examine key factors influencing the use of AI-enabled solutions in agriculture. It explores areas such as defining AI, collating evidence around the effectiveness of AI-enabled solutions, and addressing issues of ethics, equity, and governance. The study also highlights future areas of research that could improve the equitable and just use of AI-enabled solutions along the agricultural value chain.

Methodology

Scoping review

The scoping review comprised a rapid review (RR) and a narrative review. The RR utilised systematic review methodologies recommended by the Cochrane Collaboration and the Campbell Collaboration. It synthesised 51 peer-reviewed and grey literature studies, which included 35 quantitative studies, 14 qualitative studies, and 2 mixed-methods studies. The qualitative evidence was critically appraised using the NICE framework, while quantitative studies were evaluated with PROBAST, Cochrane ROB2, and ROBINS-I tools. The narrative review complemented the RR, and synthesised findings from 27 qualitative studies. It incorporated non-peer-reviewed articles, grey literature, and other sources to provide broader perspectives.

More details on the findings drawn from the RR can be found in another report, here.

Case studies

This report also presents case studies that illustrate diverse applications of AI in agriculture and highlight critical regional trends and contexts within L&MICs. These case studies provided concrete examples of AI's implementation and its impact on local communities. Regional experts informed the selection and analysis of the case studies to ensure contextual relevance and robustness.

Deep dives

Regional experts in the research team conducted targeted deep dives to examine the socio-political and governance aspects of AI implementation, focusing particularly on issues such as the digital divide and digital inclusion. These deep dives provided critical insights into local challenges and opportunities in AI adoption.

Stakeholder engagements

Stakeholder engagements were conducted to validate the findings from the scoping review and case studies. These consultations involved key actors across the AI and agricultural value chains, such as policymakers, developers, implementers, farmers, and civil society organisations. The consultations aimed to generate practical insights into the real-world application of AI innovations and the challenges associated with their implementation.

Research questions and findings

Key research questions explored in this study are: (i) defining AI, (ii) understanding the effectiveness of AI-enabled solutions, (iii) ethics and equity, and (iv) horizon mapping. The research team adopted a multi-method approach because each method would respond to different research questions. The following section presents a brief overview of findings from each research question.

Defining AI

AI is currently in the developmental phase in the agricultural ecosystem. Crop production is the primary domain targeted, with limited evidence available on livestock and aquaculture. Automation devices such as drones are being developed for weather forecasting, agricultural process management, and optimising irrigation. Machine learning technologies are advancing agricultural practices by developing classification models for disease and weed identification.

In addition to the aforementioned use cases, AI-enabled solutions are often bundled into comprehensive solutions in order to support smallholders throughout the crop production cycle. Researchers also found that AI has the potential to play an important role in the transition to Climate Smart Agriculture (CSA) solutions (which are also often provided in bundles).

Understanding effectiveness

The metrics used to measure effectiveness include productivity, food security, income, and livelihoods. A critical gap remains in assessing AI-enabled solutions in agriculture, as these technologies are still at an early stage of development. Key dimensions for assessing impact include ‘improvement in yield’, ‘decrease in cost of cultivation’, ‘increase in farm revenue’, ‘profit/loss from sale of produce’, and ‘increase in net household income’.

Ethics and equity

AI adoption in agriculture faces significant equity challenges. Structural barriers, including cultural norms and limited female participation, reinforce the digital divide. Data on digital literacy is scarce, creating a major research gap and raising the risk of exclusion. AI bias may further deepen existing disparities. Although many countries are developing AI frameworks, these mainly promote AI in general and rarely address agriculture-specific needs. To ensure fair adoption, equity must be prioritised in the development and implementation of AI for agriculture.

Horizon mapping

Short run: Actionable insights are needed to build geographically representative databases for localised solutions, creating shareable data platforms, and expanding research on L&MICs.

Medium run: Encourage inclusive collaboration among stakeholders to implement AI-enabled solutions. Promote peer-to-peer learning models, such as self-help groups and community resource persons (CRPs), to support adoption. Strengthen monitoring and evaluation of activities, and establish regulatory compliance frameworks.

Long run: Support the scaling and sustainable implementation of AI in agriculture.

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Abbreviations

3ie	International Initiative for Impact Evaluation
AAV	Autonomous Agricultural Vehicles
ADB	Asian Development Bank
AG	Agriculture
AGRO 4.0	Brazil's Agricultural Technology Program
AgTech	Agricultural Technology
AgriTech	Agricultural Technology
AI	Artificial Intelligence
AI4AI	Artificial Intelligence for Agriculture Innovation
ASEAN	Association of Southeast Asian Nations
AVPN	Asian Venture Philanthropic Network
B2B	Business to Business
B2C	Business to Consumer
BM&C NEWS	Business Management & Consultancy News
CNN	Convolutional Neural Network
COBIT	Control Objectives for Information and Related Technology
CRM	Customer Relationship Management
CRP	Community Resource Persons
CS	Case Study
CSA	Climate-Smart Agriculture
DD	Deep Dives
DDS	Digital Development Strategy
Digital Green	Digital Green (an organisation focused on digital agriculture)
ERP	Enterprise Resource Planning

EU	European Union
FAO	Food and Agriculture Organization
FCDO	Foreign, Commonwealth & Development Office
GenAI	Generative Artificial Intelligence
GPS	Global Positioning System
GSMA	Global System for Mobile Communications
ICT	Information and Communications Technology
IDB	Inter-American Development Bank
IFC	International Finance Corporation
IFPRI	International Food Policy Research Institute
IoT	Internet of Things
ISO	International Organization for Standardization
J-PAL	Abdul Latif Jameel Poverty Action Lab
KALRO	Kenya Agricultural and Livestock Research Organization
KIAMIS	Kenya Agricultural Market Information System
KICTANet	Kenya ICT Action Network
L&MICs	Low & Middle-Income Countries
LLM	Large Language Models
ML	Machine Learning
MOALD	Ministry of Agriculture and Livestock Development
MOCI	Ministry of Communication and Information Technology
NABARD	National Bank for Agriculture and Rural Development
NCB	National Computer Board (Mauritius)
NGOs	Non-Governmental Organizations
NIST	National Institute of Standards and Technology

NLP	Natural Language Processing
OECD	Organization for Economic Cooperation and Development
OJK	Financial Services Authority (Indonesia)
PBI	Picture-Based Insurance
PICO	Population, Intervention, Comparison, Outcome (framework)
PPPs	Public-Private Partnerships
Q&A	Question and Answer
R&D	Research and Development
RF & NN	Random Forest and Neural Network
RAG	Retrieval-Augmented Generation
RCC	Research Commission Centre
RR	Rapid Review
SDGs	Sustainable Development Goals
SE	Stakeholder Engagement
SHGs	Self-Help Groups
SOFA	State of Food and Agriculture
SSA	Sub-Saharan Africa
TWG	Technical Working Group
TD	Typology Development
UAVs	Unmanned Aerial Vehicles
UNDP	United Nations Development Program
USAID	United States Agency for International Development
UX	User Experience
WEF	World Economic Forum

Glossary of technical terms

Term	Definition
AI-enabled solutions	Applications of artificial intelligence are designed to support agriculture through tasks such as yield prediction, disease detection, and farm-level decision-making.
Agriculture 4.0	Transformation of agriculture through digitisation, automation, and advanced technologies to enhance productivity, efficiency, and sustainability.
Bias assessment	Process of evaluating the reliability of included studies, rating them as low, high, or unclear risk of bias.
Case study	A qualitative research method focusing on detailed examination of specific instances of AI use in agriculture.
Conversational chatbots	AI tools (often using LLMs) that provide agricultural advice to extension agents or directly to farmers.
Deep learning	A machine learning technique using layered neural networks for complex prediction tasks, e.g., crop disease detection.
Digital divide	The gap between those who have access to AI tools, internet, and digital literacy, and those who do not.
Digital literacy	The knowledge and skills needed to effectively use digital technologies, a key barrier to AI adoption among farmers.
Field trial	Testing AI-enabled solutions directly in agricultural settings, as opposed to lab experiments.
Forecast and prediction	AI use for climate/weather forecasting and determining optimal harvest times.
Horizon mapping	Forward-looking analysis of short-, medium-, and long-term pathways for AI adoption.
Machine learning (ML)	AI subfield involving algorithms that learn patterns from data to make predictions (e.g., yield forecasting).
Natural language processing (NLP)	AI techniques that interpret and analyse human language for agricultural applications like chatbots and advisories.
PICO framework	Systematic review tool (Population/Setting, Intervention, Comparison, Outcome) adapted here for agriculture.

Pilot search	Initial test searches to refine the search strategy for systematic reviews.
Precision agriculture	Farming approach using AI, sensors, and data-driven techniques to optimise inputs and outputs.
PRISMA flowchart	Standard reporting tool documenting the screening and selection process in systematic reviews.
Qualitative research	Studies using interviews, case studies, or thematic analysis to assess perceptions and impacts of AI in farming.
Quasi-experimental design	Non-randomised study approach used to evaluate AI effectiveness in real-world agricultural settings.
Rapid review (RR)	A streamlined version of a systematic review conducted within shorter timelines while maintaining rigour.
Risk of bias	Likelihood that a study's design or methods distort its findings.
Simulation study	Computer-based modelling of AI applications in agriculture, as opposed to real-world field trials.
Smallholder farmer	Farmers managing small plots, usually family labour based, producing mainly for subsistence or local markets.
SPIDER framework	Systematic review tool for qualitative research (Sample, Phenomenon of Interest, Design, Evaluation, Research Type).
Value chain (agricultural)	Stages of agricultural production, processing, and distribution where AI solutions may be applied.

1. Introduction

1.1 Background and context

The growing global population, coupled with climate change has placed immense pressure on agriculture and raised concerns about global food security (WUR 2022). AI is emerging at the forefront of an agricultural transformation described as Agriculture 4.0 (HT 2023). Agriculture 4.0 refers to the integration of Internet of Things (IoT), drones, big data, AI, and robotics to improve farm methods and promote sustainability (Javaid et al. 2022)

The convergence of agriculture and AI is happening rapidly and has stong potential to change global agrifood systems. Global interest in AI-enabled solutions for agriculture is increasing. However, evidence on their effectiveness, alignment with institutional, social and environmental contexts, and implications for equity remains limited. Recent discussions underscore the importance of examining how technology-driven solutions can enhance agricultural productivity (3ie 2024; FCDO 2023).

This landscape study has been commissioned to Athena Infonomics by the FCDO's Research Commission Centre (RCC) and 3ie due to their specific interest in understanding how AI can effectively address extreme poverty worldwide (FCDO 2023). One key area of enquiry is how these technologies can help farmers in L&MIC settings.

This research aims to provide a landscape view on AI-enabled solutions in agriculture. It seeks to generate evidence to guide policy decisions and support the FCDO's strategic investments in developing AI. The study supports FCDO's broader strategy to expand investment in AI and agriculture, ensuring that innovations are scalable and address key agricultural challenges.

Much like any other technological advancement, the benefits of AI-enabled solutions are unevenly distributed across the globe. L&MICs risk being left behind and unable to use AI to advance the SDGs and their development goals. Agriculture is a key sector in most L&MICs. It contributes significantly to the country's GDP, provides income to a large share of the population, and is critical for households' food security. However, agricultural production, especially by small- and medium-scale producers, presents a unique set of technological, socio-cultural, environmental, and biophysical challenges. Many of these challenges are long-standing, with no simple solutions. The local context in which agriculture takes place naturally also affects AI implementation. This presents actors interested in the application of AI in agriculture with a broad range of opportunities as well as complex challenges. Therefore, the main aim of the landscape analysis is to gain a larger understanding of AI-enabled solutions in agriculture, specifically in an L&MIC setting.

1.2 Study objectives and approach

The study examines the current use of AI-enabled solutions in agriculture, addresses key research gaps, and informs the existing body of evidence. The preliminary analysis identified critical knowledge gaps in the field. This underscores the need for a systematic assessment of AI applications employed to address different agricultural challenges. While AI is increasingly applied in agriculture, there is limited comprehensive analysis of how these technologies are deployed to tackle specific agricultural issues.

This study goes beyond a purely technological perspective by incorporating broader socio-economic and contextual considerations. It aims to provide a holistic understanding of the interplay between technological innovation and local agricultural systems. Much of the evidence focuses on the availability of AI tools; however, this study expands on this by examining their impact on agricultural productivity, ethical and equity considerations, adoption barriers, and future trajectories. (See Annex for details on the objective and the approach of the research)

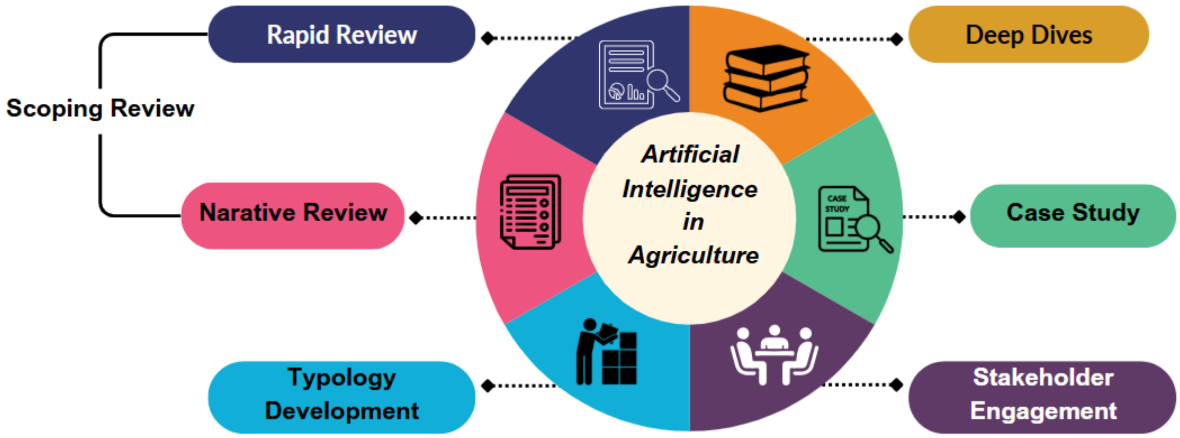
1.3 Research questions

The core research questions that guided the study reflected the broad categories investigated and the specific themes addressed within each of these categories. These questions provide a structured approach to understand the applications, effectiveness, and implications of AI technologies within agrifood systems, particularly in L&MICs. They are structured to explore the definitions and typologies of AI, assess the evidence of their effectiveness, examine the barriers to adoption, address ethical and equity considerations, and map out future trajectories (see Annex for overview of the research questions).

1.4 Methodology

The mixed method approach incorporated an RR, a narrative review, typology development, deep dives, case studies, and stakeholder engagement. Figure 1 provides an overview of the methodologies. Each methodological component was selected on the basis of its ability to address specific research questions while considering the strengths and limitations associated with each method (see Annex for detailed explanation of each of the methods).

Figure 1: Mixed-methods approach



1.5 Limitations and mitigations

While the study provides insights across methodologies, it is important to acknowledge some of its limitations (see Annex for limitations across the different methodological approaches employed in the study).

2. Findings

2.1 Defining AI

To understand the influence of AI on agriculture, it is essential to examine its current stage of development. This analysis considers the deployment phase, whether in research or field application. It also examines key use cases, target problems, AI types, and the diverse stakeholders within the ecosystem. This includes users, beneficiaries, deployers, and funders.

The current stage of development of AI-enabled solutions and their deployment in the field

- The research found growing interest in the use of AI for agriculture. Machine learning led among interventions, followed by automation, robotics, deep learning, neural networks, and predictive AI. Generative AI was largely absent, reflecting its early stage of development and limited evidence, as confirmed by stakeholders and case studies. For example, Digital Green's Farmer.Chat app (see Annex for details).

Stakeholders confirmed the early-stage nature of most agricultural AI applications. In India, they noted that many solutions remain in research and development (R&D), with few advancing to piloting or wider implementation. This distinction matters: R&D focuses on designing and refining technologies, while piloting tests them in real-world settings. The limited movement beyond R&D highlights a major challenge in converting AI's potential into practical, scalable solutions for farmers (see Annex for details).

> In India, the majority of AI applications in agriculture remain in the pilot stage and are largely experimental. The solutions mainly focused on research and development, and usually don't stick beyond the pilot phase. However, there are emerging applications, particularly in crop production and addressing nutrient deficiencies, that show promising potential.
>
> \- Dona Mathew
> Digital Future Lab

Current use cases and implementations of AI

- AI-enabled solutions in agriculture offer farmers the opportunity to revolutionise their practices with cutting-edge technologies. As AI advances, it aims to enhance productivity, sustainability, and efficiency across various farming practices based on specific use cases.

These technologies span a wide range of applications, including machine learning, automation, robotics, and generative AI. AI helps optimise resource use (water, fertilisers, pesticides) and supports activities such as pest detection and crop health monitoring. AI-powered systems can identify threats and suggest mitigation strategies in real time.

Often, AI-enabled solutions are provided as a bundled service. In agriculture, bundling refers to the practice of combining multiple agricultural inputs, services, or technologies into a single package. This is done to improve access, adoption, and effectiveness, particularly for smallholder farmers (Fleischer 2011). Scaling such digital innovations requires a holistic and strategic approach (Kirina et al. 2022). This has also been corroborated by findings from the stakeholder discussions. Several startups in L&MICs, such as Cropin and Fasal from India, XAG from China, and Mertani from Indonesia, are providing precision agriculture solutions. They employ a combination of AI and automation-based technologies, such as drones and robots, for problems such as detecting and managing pests and diseases, and optimising irrigation or crop harvesting. According to Digital Green, end-to-end solutions are crucial and ensure that farmers receive advice and assistance throughout the crop production process (for primary use cases of AI-enabled solutions in agriculture, see Annex).

The findings demonstrate clear progress in AI applications for crop disease detection, productivity enhancement, and improved agricultural decision-making. The predominance of machine learning and automation in AI interventions reflects the current technological focus on precision agriculture. The study also indicates that AI is making measurable contributions to agriculture in L&MICs, particularly in areas like yield optimisation, disease prevention, and resource efficiency.

Current AI deployment in the field

- This study reveals that the integration of AI in agriculture is still in its early stages. Current implementations are largely experimental. Applications such as crop monitoring, yield prediction, and pest control are being tested on a limited scale.

The study explored four AI builds that are currently being deployed in the field. One of the cases is a global example of Digital Green, whose AI chatbot has been deployed across the world. The remaining three are region-specific examples: Kenya’s Tulime Tuvune, Brazil's SciCrop, and India’s Saagu Baagu.

Global case: Digital Green's Farmer.Chat

Farmer.Chat is an AI-powered chatbot developed by Digital Green to provide extension agents and smallholder farmers with contextual, localised, and actionable agricultural advice. Since women are often left out of traditional advisory channels, Digital Green aims to reach 55 percent of them through Farmer.Chat. The chatbot leverages retrieval-augmented generation (RAG), large language models (LLMs), and real-time data integration to support farmers in making informed decisions. This includes weather data integration (using Tomorrow.io), crop and pest diagnostics, and treatments (using Plantix).

From a gender inclusion perspective, the core challenges that Farmer.Chat aims to address include:

- The gender yield gap: Women farmers produce 20–30 percent less than men due to limited access to advisory services, lower adoption rates, and barriers to implementing solutions.
- Information asymmetry: Even when women receive advisory services, these are often less relevant or actionable due to labour constraints, financial limitations, and gender norms.
- Trust and adoption issues: Farmers require trusted, socially validated, and specific guidance tailored to their needs.

Kenyan Tulime Tuvune

In Africa's smallholder agriculture, most AI-enabled solutions focus on traditional development interventions such as advisory services, market access and finance. Tulime Tuvune, a locally developed solution, uses AI to provide farmers with tailored expert advice. Kenyan chatbot Tulime Tuvune is an AI-powered farming assistant that is designed to support smallholder farmers with everyday decisions about agriculture. Deployed in 12 out of 47 counties in Kenya, the solution has been downloaded by 4568 farmers. Tulime Tuvune's primary focus is to address critical challenges in agriculture, such as market linkages, disease surveillance, and post-harvest losses. This is done through a platform that is accessible via WhatsApp. The solution uses agricultural data from Kenya Agricultural Market Information System (KIAMIS) managed by the Kenya Agricultural and Livestock Research Organization (KALRO). It also integrates information and data about weather forecasts, news about pests and diseases, and changing rain patterns. These data are gathered from trusted sources like FAO, and the Ministry of Agriculture and Livestock Development (MOALD). The system uses this information to deliver actionable insights.

Tulime Tuvune is an AI-powered farming assistant that uses WhatsApp to deliver tailored agricultural advice, integrating data from KIAMIS, weather forecasts, and updates on pests and diseases. It helps smallholder farmers manage crop production, market linkages, and post-harvest losses.

The platform employs various AI technologies, including:

- **Natural Language Processing (NLP):** Facilitates communication between farmers, extension officers, and the AI model through a chatbot, mainly in English and Kiswahili.
- **Image and audio analysis**: Allows users to diagnose crop diseases and pests by submitting images or audio descriptions via WhatsApp. The model then responds through the same channel with insights about the diseases and potential mitigation strategies, which also include input recommendations. One weakness with this feature is that some responses may be generalised rather than specific disease

diagnoses. This may not be so useful for an average farmer, as it provides insufficient insights into what they are seeking.
- **Retrieval-Augmented Generation (RAG):** Ensures localised, context-specific advice from credible sources. For instance, the solution can retrieve farm-specific weather forecasts if the current GPS location is provided. A farmer can also type the letter M to access a menu with guidance on any other services provided by the solution provider.
- **Machine learning models:** Provides personalised recommendations and predictive insights on crop. For instance, the platform can provide information about the crop varieties that are well-suited for specific climates and soil types. The challenge with this feature is that it requires comprehensive data on crop varieties, weather, and soil types, which is not always available for some regions.
- **Predictive analytics (under development):** Forecasts weather patterns, market trends, and crop performance.

Brazilian SciCrop

SciCrop is a Brazilian AI-driven platform designed to enhance precision agriculture through the use of machine learning and data analytics. It offers real-time decision support to two customer types: production customers (farmers of all sizes, as detailed in Annex Table 1) and business customers such as banks and financial institutions. The platform provides insights on crop management, pest control, soil health, irrigation, and weather forecasts. SciCrop aims to enhance food security in Brazil, a major global food exporter, by improving farming efficiency. The platform uses AI to boost agricultural productivity by optimising resource allocation (water, fertilisers, pesticides) and predicting crop diseases. SciCrop applies machine learning and data analytics to guide crop management, soil health, irrigation, pest control and weather forecasting, providing real-time insights to improve productivity and sustainability. In a personal interview, José Damico, CEO of SciCrop, explained the company's four subscription-based products: three ready-to-use dashboards and InfinityStack, a customisable dashboard developed on demand for each client (See Table 2 in Annex). Together, these products can generate four types of analysis. For more information, please (see Table 13 in Annex).

SciCrop designed and developed the three dashboards and InfinityStack, a comprehensive product offering dashboards, maps, chatbots and algorithms, supported by robust infrastructure and services. The company drew on years of consulting experience and its algorithm portfolio to create these solutions (see Figure 19 in Annex).

South India's Saagu Baagu

One such example in the Asian context is Project Saagu Baagu. Reports indicate that this pilot was a massive success, significantly improving yields for smallholders in Telangana (Forbes 2024). Led by the Government of Telangana, India, Saagu Baagu is one of the projects under the WEF's Artificial Intelligence for Agriculture Innovation (AI4AI) initiative. It aims to "transform the state's agriculture by leveraging emerging technologies in a scalable, inclusive, and sustainable" manner. The project started with the launch of an 18-month pilot programme in 2020 and is expected to be completed in 2025. It targets five districts in the Indian state of Telangana: Khammam, Mahabubabad, Gadwal, Suryapet, and (rural) Warangal (WEF 2023a).

Climate change, through increased pest attacks and droughts, is significantly reducing chilli farmers' productivity and income. The Saagu Baagu project addresses this challenge by providing 7,000 enrolled farmers with technology and support to mitigate the effects of climate change. The project offers comprehensive services throughout the crop cycle, starting with advisories disseminated by trained CRPs via videos and in-person sessions. By March 2023, over 17,000 farmers had attended sessions on pest and disease management and received AI-based chatbot advisories.

The pilot was conducted in the Khammam district, and it mainly targeted the chilli crop. Digital Green was the implementation partner within a consortium that included three agri-startups: AgNext, KrishiTantra, and Kalgudi. KrishiTantra provided AI-based soil testing services to most of the enrolled farmers. AgNext deployed quality testing machines, issued certificates to nearly 4,000 farmers by March 2023, and conducted trader orientation sessions to ensure that the certificate is accepted. Kalgudi's e-commerce platform enabled business-to-business and business-to-consumer sales of processed red chilli, listing 5,000 farmers.

The Saagu Baagu project supports smallholder chilli farmers in adapting to climate change impacts such as pests and droughts, while optimising crop productivity. It provides AI-powered chatbot advisories for pest and disease management and offers training sessions through CRPs.

The Saagu Baagu project, led by the Government of Telangana, India, successfully implemented AI chatbots to improve smallholder farming through a public-private partnership. Startups like AgNext, KrishiTantra, and Kalgudi used AI-powered solutions to enhance soil testing, provide crop advisories, and improve post-harvest practices. AI-based soil tests helped farmers optimise irrigation and fertiliser use, while WhatsApp chatbots delivered pest and disease management advisories in the local language. AgNext's AI-driven quality testing machines enabled farmers to obtain certificates for their produce, improving market access. Kalgudi's e-commerce platform enabled the direct sale of processed chilli crops to businesses and consumers. Digital Green supported the implementation by coordinating the pilot and scaling stages. The involvement of CRPs ensured that farmers were engaged and trained in using these digital tools. The project targeted both male and female farmers and drew on academic expertise from Professor Jayashankar Telangana State Agriculture University, to ensure the tools were locally relevant and effective.

Users and beneficiaries

ASEAN defines users as "an entity or person (internal or external) that interacts with an AI system or an AI-enabled service, and can be affected by its decisions" (ASEAN 2024). On the other hand, beneficiaries are those who will derive some benefit from the implementation of the AI. Users and beneficiaries in this case could include smallholders, medium-scale farmers, extension agents, international market actors, local market actors, and non-human agents.

- A key finding is the underrepresentation of low-income countries (LICs) and smallholder farmers, who are the most vulnerable to agricultural challenges. Nearly half of the studies failed to specify the income category of their target regions. Neither did they explicitly identify smallholder farmers as users. As most studies focus on AI-enabled solutions still in the R&D or pilot phase, they often lack nuanced perspectives from users and beneficiaries.

Box 1: Users of Tulime Tuvune

Tulime Tuvune is designed to support a diverse range of stakeholders:

- Smallholder farmers can use the solution directly for insights that address their farm needs (e.g., disease and pest identification and monitoring, crop performance insights, and weather forecasting).
- Agritech actors (e.g., tech developers and research institutions) and agripreneurs (e.g., agrovets) can use data collaboration opportunities and recommendation algorithms to innovate complementary tools and market farm inputs.
- Extension officers use the solution to complement their advisory roles. For instance, if they cannot identify a new disease or a pest in their locality, they can use the solution to get insights about that disease.

All this potentially contributes to improved farm decision-making and livelihoods for smallholder farmers. Agricultural technology actors can benefit from data collaboration. Agripreneurs and extension officers can benefit from marketing farm products such as fertilisers, agrochemicals and other inputs, along with complementary advisory insights.

Box 2: Users of SciCrop

SciCrop, offers on-demand solutions for smallholder and medium-scale farmers, but 70 percent of its business comes from large enterprises. These enterprises exert significant influence over smaller farmers by shaping market conditions, supply chains, and access to technology. Large enterprises using SciCrop's solutions set benchmarks for efficiency, data-driven decision-making and resource management. These benchmarks often compel smaller farmers to adapt in order to remain competitive. As suppliers or partners to these enterprises, smallholder and medium-scale farmers also experience downstream effects—both positive and negative—of operational improvements. These include optimised logistics, better forecasting and greater sustainability. SciCrop actively gathers client feedback, initially through interviews that inform product development, and now continuously via telemetry and metadata collection.

Box 3: Users of Saagu Baagu

Smallholder chilli farmers are the primary users and beneficiaries of Saagu Baagu, the Asian case study. The shift from cereal to commercial crop farming in Telangana has created significant challenges for smallholders. Commercial farming demands higher investment and carries greater risks for farmers, creating a highly competitive market. While larger farmers benefit from economies of scale, small farmers face disproportionately high costs and low revenues. This reduces their profits (WEF 2023a). The report also notes that "the ubiquity of small-scale farmers in the Indian agrarian landscape has not translated into better credit facilities for them." They aim to improve this aspect by providing smallholders, "especially women", much-needed formal credit through data-driven credit scoring and digital financial services.

Role of other stakeholders

This report also acknowledges the crucial roles of funders, developers, and deployers in the agricultural AI ecosystem. Funders are diverse stakeholders who provide capital for developing or deploying AI. Deployer is "an entity that uses or implements an AI system, which could either be developed by their in-house team or via a third-party developer". A developer is "an entity that designs, codes, or produces an AI system". (ASEAN 2024)

Agritech Startups: Agrifoodtech startups have become the main developers of AI-enabled solutions in agriculture. In Asia, for example, Singapore-based IntelloLabs uses AI-powered image recognition to assess the quality of produce, helping to ensure quality control and reduce food waste. In India, WayCool stands out as the leading agricultural startup, targeting the entire crop production process—from cultivation and processing to distribution and sale (Waycool 2023). Cropin and Fasal from India, XAG from China, and Mertani from Indonesia are startups that offer solutions for precision agriculture. They employ a combination of AI and automation-based technologies, such as drones and robots, to detect and manage pests and diseases, and to optimise irrigation or crop harvesting. Figure 2 provides an overview of AgriTechs found across Asia.

Figure 2: Agrifood tech startups in Asia

The adoption of AI in SSA's agriculture is rapidly expanding, with applications that aim to improve productivity, efficiency, and farmer livelihoods. Notable examples are illustrated in Figure 3.

Figure 3: The adoption of AI in Sub-Saharan Africa (SSA)

Funding and investment landscape

Research funders

The narrative review identifies current funders of agricultural AI research. Funding patterns across the reviewed studies revealed that just over half (53.85%, n=14) explicitly disclosed their funding sources. Notably, these studies benefited from the support of well-established international organisations like the International Development Research Centre (IDRC), the World Bank, the Gates Foundation, and The MasterCard Foundation. This highlights a trend of reliance on both national and international funding (see Table 6 in Annex).

- Funding is, thus, a critical issue, with nearly half of the studies lacking external funding. This lack of funding could restrict the depth and scope of AI research in L&MICs and limit the ability to conduct large-scale, long-term studies. The absence of detailed reporting on funders also raises questions about transparency and potential conflicts of interest in AI development.

Non-research AI funders in agriculture

- Beyond traditional research funding, the study identified 'non-research AI funders' who invest in the practical development and deployment of AI technologies in non-academic settings. This underscores the need for a broader analysis of AI funding sources.

WEF representatives noted the importance of catalyst funders in the scaling of public-private partnerships (PPPs). According to them, catalyst funding is key because it is difficult for smallholder farmer to achieve profits during the first few years of implementing agri-tech technologies. Consistent funding streams are essential for the sustained development and deployment of AI in agriculture. The funding ecosystem for AI in agriculture is a mix of philanthropic, corporate, and venture capital investments. Key investors include the Asian Venture Philanthropic Network (AVPN), Google, Nouryon, AgEye, and Salesforce. Nouryon's focus on automated indoor farming in India, alongside European and North American investments in South East Asia, shows the global scope of these efforts. Yet, in SSA, concerns remain that funding may prioritise technology and data productivism over local needs. This raises two risks: policies being shaped by capitalist interests, and the exclusion of critical stakeholders such as academia and civil society from AI discourse. The unequal power dynamics between resource-rich and resource-poor countries also pose a threat to the relevance and equity of AI-enabled solutions for smallholder farmers. Figures 4 and 5 provide an overview of funders and investors in Asia and Latin America.

Figure 4: Funders and investors in South Asia

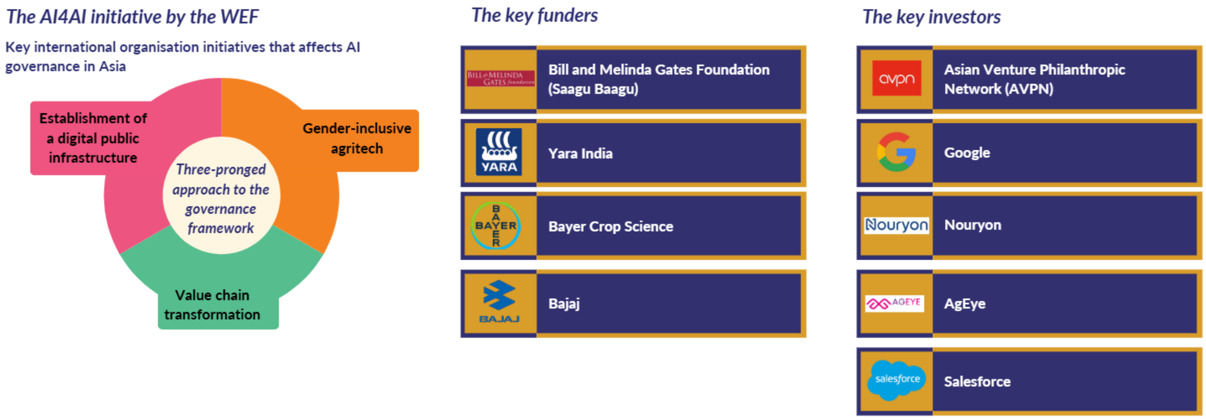
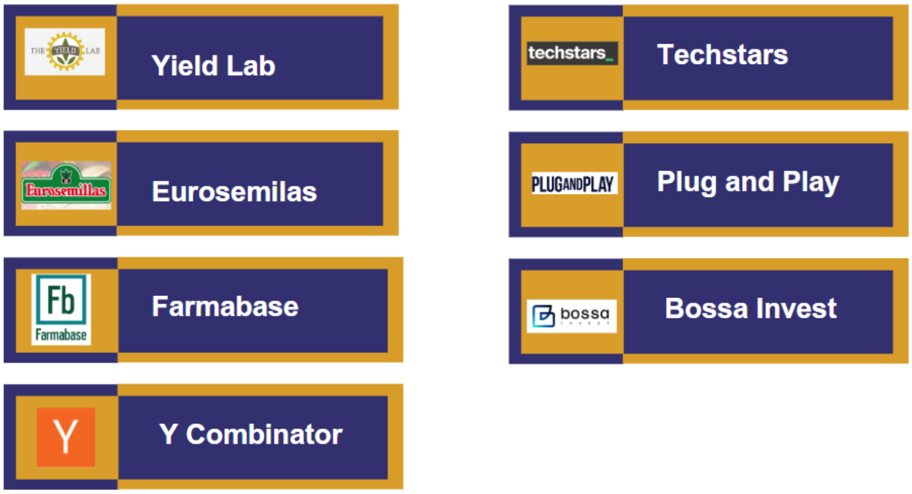


Figure 5: Key investors in Latin America



Knowledge dissemination and ecosystem development

International organisations such as the Inter-American Development Bank (IDB) play a crucial role in enabling the regional AgriTech ecosystem through the development of knowledge products. For example, the IDB's pioneering Agritech Innovation Map in Latin America and the Caribbean, along with related reports, has highlighted digital agriculture opportunities for smallholder farmers. These reports showcase the rise of digital advisory services, smart farming, and the use of AI and big data analytics. Moreover, their collaborations with organisations like Global System for Mobile Communications and Incofin Foundation have further contributed to the dissemination of knowledge and the promotion of digital disruption in the agricultural sector. Significant investment in the region, led by investors such as the Yield Lab, Eurosemillas, and Y Combinator, highlights the growing interest in agritech across Latin America and the Caribbean.

A conversation with Dr. Praveen Rao Velchala, a representative from the Saagu Baagu project, highlighted the critical issue of interoperability between farmers and agritech professionals. This gap stems from a lack of agricultural knowledge among agritech professionals and a lack of technological understanding among farmers and farmer cooperatives. According to him, universities can bridge this divide by providing agritech experts with the necessary knowledge. This includes understanding how to assess the value of technology in the field through rigorous, two-season testing. Universities can also help refine these technologies by educating agritech entrepreneurs about key use cases prioritised by farmers in the region. He also suggested that by working with field officers, universities can aid farmer training programmess and capacity building initiatives.

The role of governments in setting up digital infrastructure is also very important. With the Asian case study, Dr. Praveen Rao and representatives from WEF recognised that Telangana was a hotspot for an initiative such as AI4AI. Proactive government initiatives and strategic partnerships created favourable conditions for the location. WEF representatives also stressed the importance of progressive state attitudes and policies in ensuring the success of such a public–private partnership (see box in Annex).

SDG reflections

The development of chatbot advisories, like Farmer.Chat, Tulime Tuvune, and Saagu Baagu demonstrate a commitment to providing localised, real-time solutions to smallholder farmers. Empowering farmers with access to information and technology is crucial for achieving SDG 1 (No Poverty) and SDG 8 (Decent Work and Economic Growth). Digital platforms like SciCrop support SDG 9 (Industry, Innovation, and Infrastructure) by enhancing productivity and sustainability through data analytics.

AI has significant potential to advance climate-smart agriculture and support SDG 13. However, it is important to address sustainability concerns and opportunity costs to ensure alignment with SDG 12 (Responsible Consumption and Production).

The observed underrepresentation of users and beneficiaries, particularly smallholder farmers and LICs, highlights a critical gap in achieving SDG 10 (Reduced Inequalities). Engaging these stakeholders in developing and deploying AI-enabled solutions is essential for equity. Funders, developers, and deployers play a crucial role in achieving a multi-stakeholder approach that is necessary for the advancement of AI in agriculture. The funding gaps, particularly in research, pose a challenge to achieving SDG 9 (Partnerships for the Goal). Increased investment from research funders like IDRC and the World Bank, alongside non-research funders like the Gates Foundation and AVPN, is crucial for fostering innovation and scaling impactful solutions.

2.2 Understanding effectiveness

Effectiveness refers to the extent to which AI-enabled solutions achieve the intended outcomes defined by their implementers. However, the landscape study offered limited insights into the effectiveness of AI in agriculture, primarily due to a lack of available evidence. Stakeholders suggested that this gap stems from AI in agriculture being an emerging field, with many tools still in development or limited to small-scale pilot testing. As a result, there is limited data on key effectiveness indicators such as productivity, food security, and impacts on income and livelihoods. Findings from the rapid review echoed this, as most studies focused on the accuracy of AI models rather than their broader outcomes. Only certain regional case studies, such as Asia's Findings from the RR echoed this, with most studies focusing primarily on the accuracy of AI models rather than their broader outcomes. project and Africa's DigiFarm, present a framework for impact assessment (see Annex for details).

The effectiveness of AI in agriculture cannot be measured solely by technological implementation; it must also account for how these innovations fit into the farmers' daily practices, how farmers understand technology, and their willingness to adopt it. As developers and deployers continue to engage with farmers directly, technology can offer valuable support. However, that does not automatically solve all the challenges they face. AI-enabled solutions must be audited after implementation to ensure effectiveness on the field.

Reflection on SDGs

This research focused on productivity, food security, income, and livelihoods, aligning directly with SDG 2 (Zero Hunger) and SDG 1 (No Poverty). The critical gap that was identified in effectiveness measurement is a significant challenge, especially because AI-enabled solutions are still in the developmental stage. This lack of data limits researchers' ability to assess AI's contribution to these crucial SDGs.

2.3 Ethics equity and governance

The integration of AI in agriculture offers a transformative opportunity to enhance productivity, sustainability, and resource management. At the same time, applying AI-enabled technologies raises important ethical and equity concerns. The research team aimed to produce a study that not only mapped AI tools to agricultural challenges but also provided a nuanced narrative on inclusivity. This approach uncovered layered discussions on the digital divide, data accessibility, community-led practices, governance, and gender.

- As AI technologies advance, it is essential to develop inclusive solutions that accommodate various regions, cultures, and socioeconomic backgrounds.
- All users, regardless of their background or farm size, should be able to benefit from innovations in agriculture.
- A fundamental way in which the digital divide manifests is through the lack of sufficient financial resources to access AI-enabled solutions.

SciCrop, in Brazil serves as an interesting example related to digital accessibility. They have made important strides in localising content and interface. They are working on an intuitive no-code or low-code platform that integrates and applies any data type to a wide range of known algorithms and models. They are focused on making it more accessible (BM&C NEWS, 2024). Moreover, Farm.Chat the Digital Green advisory, provides farmers with localised solutions for farm decisions in local languages, significantly improving accessibility for a broader audience.

> "There are still gender barriers that exist, such as access to the actual phone. Often, farm ownership is male, but the actual person working on the farm is female. So, what is evident is that the man has the phone and uses it, but the woman doesn't have access to the phone to access the data. However, women are more receptive to technology in general. We've seen that the smartphone platform is a limitation, as you can only do so much work with a platform phone. It's challenging because not only does one solution not fit all, but not even one country. You need scalability, and smallholders don't have that kind of wealth or resources to easily adapt to one-size-fits-all solutions."
>
> -Tippins Stuart, FAO
> Stakeholder Engagement Workshop

It is crucial to consider the role of AI bias (definition in Box 8) in exacerbating equity-related issues. Research shows that generative AI-enabled solutions demonstrate bias, and numerous organisations have come under public scrutiny for GenAI output that exhibits gender biases (Rockefeller Foundation 2024). Existing research demonstrates that chatbots are likely to discriminate against women and minorities (Loukides 2024).

Box 4: What is AI bias?

AI bias refers to AI tools that systematically yield less favourable, unfair, or harmful outcomes when interacting with members of specific demographic groups. This is often termed disparate impact. Biased AI chatbots can therefore either (1) perform less accurately and/or (2) treat people less favourably based on a sensitive characteristic such as race, gender, age, or religion. It should be noted that many countries have defined demographic attributes upon which it is illegal to discriminate. Organisations developing AI-enabled solutions should research which attributes are defined as sensitive in the countries where they plan to operate (Mancombu 2024).

- AI bias exacerbates equity issues. However, appropriate governance and regulatory measures can help mitigate these challenges by ensuring compliance. The following section examines the role of governance and existing standards.

Governance

International regulations mandating AI governance are evolving rapidly: COBIT (Control Objectives for Information and Related Technology) (ISACA 2025), NIST (National Institute for Standards in Technology) (NIST 2021), European Union (EU), AI Act Article 9 (Risk Management System) (EU Artificial Intelligence Act 2025), ISO (International Organization for Standardization) (ISO 2022), and For Humanity (For Humanity 2025) are examples. These frameworks share a common focus on risk management: identifying risks early, mitigating them, and managing residual risks through systems, policies, and practices. International organisations are also rapidly developing responsible AI guidance, data policies, and ethical frameworks to provide the foundations needed for integrating AI into development efforts (Vota 2024). Strong thought leadership in this space is being operationalised for development projects. Notable examples include USAID's Managing Machine Learning Projects in International Development, USAID's AI Ethics Guide (USAID 2023), and GIZ's Responsible AI Assessments (Open for Good 2025) .

- Governments hesitate to create policies in this sector due to the high costs associated with implementation and monitoring, particularly when outcomes remain uncertain. As a result, smallholders may struggle to sustain climate-smart agriculture activities in the long term (Fröhlich et al. 2013). Are these obstacles conquerable? To answer this, it is essential to examine the specific circumstances of developing countries.

The research team, comprising regional AI experts, compiled excerpts on the state of governance mechanisms across Latin America, the Caribbean, Africa, and Asia.

Latin America

FAO estimates that there are 16.6 million smallholder farms throughout Latin America where approximately 60 million people live and work (FAO 2022a). Smallholder farms are thus, at the centre of AI-enabled solutions offered by agritech startups, whose varied approaches address farmers' needs. Although women play a vital role in the sector, they remain underrepresented in adopting digital agriculture solutions. This underrepresentation is especially evident when providers fail to integrate a gender perspective into the development and deployment of digital tools, including AI systems (IDB 2019). Additionally, the rural workforce faces a significant skill gap as technological advancements reshape the economy. Many agricultural workers, particularly women, lack the digital skills needed to access both digital tools and better job opportunities (FAO 2022a).

Even though there is a widespread lack of regulations governing the use of AI in agriculture in Latin America and the Caribbean, Brazil's Ministry of Agriculture and its Ministry of Science, Technology, and Innovation are taking action. Through the AGRO 4.0 programme, they are identifying AI-enabled solutions for the federal government to process data, support decision-making, and automate tasks using agricultural software, smart sensors, and autonomous vehicles (Martinez 2024). This is setting an example of good practice for other countries in the region.

Sub-Saharan Africa

Over 80 percent of agricultural farms in SSA are smallholder farms, with agriculture contributing 15 percent of the total GDP (OECD 2016). Agriculture employs more than half of the population, with at least half of this labour force being women. Women's economic contribution through agriculture could reach US$2.9 trillion by 2030 (Jahic 2024).

Currently, AI-enabled applications and platforms such as UjuziKilimo (Ujuzi Kilimo n.d.), Tula, AGIN, Farmer.Chat, and Apollo Agriculture are operating at scale in the SSA agricultural sector. These solutions are helping farmers access information, access markets, identify crop diseases, and access inputs, credit, and crop insurance. Other applications help decode patterns in farmers' activities and generate insights based on the combined data (Foster et al. 2023). With increasing investment in AI and agritech in Africa, more AI-enabled applications for on-farm production and marketing within value chains are expected to emerge. For instance, TensorFlow, Google's AI open-source library, is being used to monitor crop diseases and pests. Various farms and companies in South Africa are also using drones for early pest and disease detection (Africa Drone Kings 2023; Consultancy.co.za 2024).

There are continental policies, conventions, and frameworks that support the use of AI and emerging technologies for economic transformation of different sectors, including agriculture. These include the Africa Agenda 2063 (African Union n.d.), the Africa Digital Transformation Strategy 2020–2030 (African Union 2020), and the African Union Malabo Convention on

Cybersecurity and personal data protection in Africa (African Union 2014). Across the publicly available national AI plans from Mauritius (National Computer Board (NCB) of Mauritius 2018), Rwanda (Ministry of ICT, Rwanda 2022), Senegal (UNDP 2022), Benin (Ministry of Digitalization and Digital Affairs, Benin 2023), Kenya (Adams 2025), and Zambia (Ministry of technology and science 2024), there is a unanimous push for investment in, and adoption of, AI in key sectors such as agriculture. Kenya has introduced guidelines focused on promoting the adoption of AI, though these aim more at encouraging uptake than governing AI itself (Owino 2022). Zambia has proposed including diverse actors in technical working groups across key sectors, including agriculture, to strengthen public participation in implementing its AI strategy (Ministry of technology and science 2024).

Asia

The Asian agricultural sector faces the dual challenge of meeting rising food demand amid population growth and urbanisation (Greenhouse Accelerator Program 2024), and mitigating the impacts of climate change (Thailand Business News 2024). The Asian Development Bank's 2021 report notes that shrinking rural populations and a rise in climate disasters have hindered agricultural productivity (ADB 2021). Digital agriculture, and particularly AI-powered solutions, are seen as promising tools to address these challenges. However, Asian agriculture is dominated by smallholder farmers who often lack access to modern technologies, quality inputs, and market information (Mazhari 2023). They are also the most affected by the digital divide because of low literacy, inadequate digital infrastructure, gender inequalities and the prohibitive costs for investing in digital hardware and software that is agriculture-specific (Herdiyeni 2024). At the same time, competition with large-scale producers for advanced AI-based solutions—such as automation and robotics—further threatens their livelihoods (Ferris 2013).

The growing demand for AI in agriculture highlights the need for clear regulation to protect all stakeholders, particularly vulnerable groups such as smallholder farmers. These regulations need to address bottlenecks such as the digital divide and data privacy concerns due to the use of AI (Greenhouse Accelerator Program 2024).

The most recent attempt at governance of AI in Asia is the February 2024 release of the ASEAN Guide on AI Governance and Ethics, which is a crucial step toward mitigating AI risks in the region (ASEAN 2023). These voluntary guidelines foster collaboration and set the stage for broader discussions. The framework follows widely accepted AI principles and emphasises human-centred AI, transparency, fairness, privacy, security, and environmental sustainability. It points towards governance methods such as internal governance, determination of the level of human involvement in AI decision-making, operations management, and stakeholder interaction. It recommends the establishment of national and regional governance mechanisms, including an ASEAN Working Group on AI Governance, to foster a robust AI system. Additionally, it provides practical guidance for organisations on how to implement AI responsibly.

In December 2023, both the Ministry of Communication and Information Technology (MOCI) and the Financial Services Authority (OJK) in Indonesia released ethical guidelines for AI. It emphasised responsible and trustworthy AI development, and use in various sectors (Herbert Smith Freehills 2025).

The MOCI draft notes the “values of AI Ethics which shall be adhered to in the use of AI technology, namely (i) inclusivity, (ii) humanity, (iii) security, (iv) democracy, (v) transparency, and (vi) credibility and accountability.”

Singapore’s National AI strategy of 2023 promotes “set[ting] forth a systematic and balanced approach to address generative AI concerns while continuing to facilitate innovation.” However, while Singapore has guidelines for AI, there is an absence of clear regulations, or a regulatory body that ensures these guidelines become enforceable law (Jones and Chang 2024).

While Malaysia has a very comprehensive guide on AI governance frameworks, it fails to address sector-specific agricultural concerns and potential adverse impacts of AI use, such as increased digital divides. Malaysia recently launched a national AI office to act as a central hub for policy and regulation, overseeing strategic planning, research, development, and regulatory oversight (Reuters 2024).

Some critical gaps in existing regional and global governance: There are also critical observations regarding existing AI strategies and policies. First, these strategies are anticipatory and techno-optimistic, presenting AI as having unprecedented potential to revolutionise agriculture, food security, and related areas such as climate action. Second, while they focus on reimagining economic growth by investing in youth (McKinsey Global Institute 2023), they remain largely silent on contextual challenges—such as data quality and governance, smallholder farming and indigenous farm practices—that are specific to AI technology in agriculture (Olabimpe Banke Akintuyi 2024).

See annex for key insights on gaps in governance across the region.

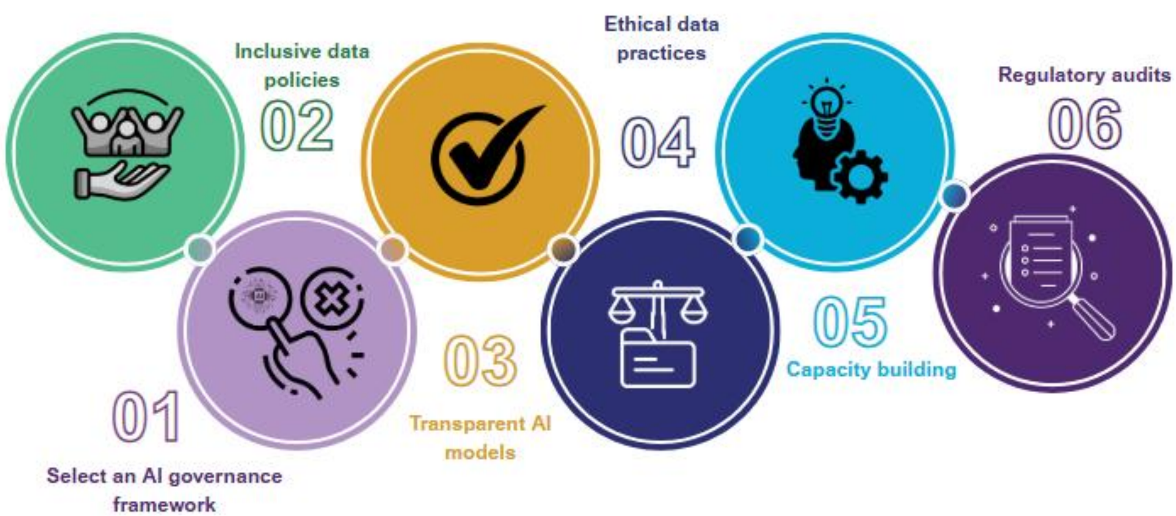
Ethical AI principles in agriculture

Governance standards are key to operationalising ethical dimensions. As noted in Annex in Table 3, there are significant gaps in existing governance standards. The table details common AI principles and defines them. It then provides examples of challenges in the agricultural sector along with potential solutions. (See Annex for details on Ethical AI principles, challenges, and potential solutions in agriculture)

To strengthen AI governance in agriculture and uphold ethical standards, the following recommendations are proposed:

- **Select an AI governance framework**: Use an AI governance framework as a wraparound, driving discussion and decision-making throughout the AI development process.
- **Inclusive data policies**: Ensure datasets are representative of diverse farming communities, and avoid bias against smallholder farmers.
- **Transparent AI models**: Mandate explainable AI systems so that farmers understand how decisions are made.
- **Ethical data practices**: Implement strict data privacy laws to protect farmers' rights and prevent data exploitation.
- **Capacity building**: Invest in digital literacy and technical training for farmers to ensure meaningful participation.
- **Regulatory audits**: Evaluate AI systems regularly to assess risks, and compliance with ethical guidelines.

Figure 6: Recommendations to build AI governance practices that best reflect ethical AI in the context of agriculture.



A good example of AI governance is Digital Green's efforts towards governing Farmer.Chat. Digital Green began exploring responsible AI practices to test, assess, and improve Farmer.Chat's gender responsiveness. Digital Green's ethos around AI development for agriculture focuses on (1) keeping humans in the loop, when possible, (2) open-sourcing their technology (Digital green 2024), and (3) being open and transparent about build processes, iterations, and learning (Economic Times 2024).

While exploring Farmer.Chat, the researchers learnt about two responsible AI practices that Digital Green have adopted. These practices are as follows:

- Red teaming plays a key role in AI governance by stress-testing models to expose biases, security risks, and unintended harms. This process helps ensure systems perform reliably across diverse groups and prevents the exclusion or exploitation of vulnerable populations.
- Similarly, golden Q&A datasets—carefully curated question-answer pairs—help improve AI fairness and accuracy. These datasets are designed to reflect real-world diversity. They ensure that AI systems provide relevant, unbiased, and accessible information, even for those with limited digital access.

Critical reflections

- Several methodologies of the study revealed a significant gap in assessing AI governance, particularly in the practical application of AI in agriculture.
- A key learning is the demonstrable lack of robust agricultural governance mechanisms across regions, particularly those affecting marginalised communities, such as smallholder farmers and women.
- None of the regions have implemented regulatory frameworks with penalties for non-compliance. The global analysis shows that existing governance frameworks fall short on sustainability and inclusivity.
- Ethical AI principles form the bedrock of responsible AI development and deployment. Principles like fairness, transparency, accountability, privacy, safety, sustainability, inclusivity, and autonomy provide a moral compass for navigating the complex landscape of AI in agriculture.
- Applying these principles in practice requires careful consideration of the specific challenges and opportunities presented by different AI applications. For example, ensuring fairness may involve addressing biased data that affects smallholder farmers, while promoting transparency might require that AI-driven recommendations remain understandable to farmers.
- Specific AI use cases in agriculture, such as AI-enhanced extension services, AI-powered pest detection, and intelligent irrigation management, illustrate the diverse

range of governance challenges. These examples underscore the need for localised solutions tailored to the unique context and community of each region.

- Accessibility remains a key concern, particularly around digital infrastructure, literacy, and language barriers.
- Model validation, environmental safeguards, and equity considerations are also crucial for ensuring that AI technologies are deployed responsibly and sustainably.

Findings from regional deep dives conducted in Latin America, SSA, and South Asia reveal distinct challenges and opportunities in each region.

- Latin America grapples with issues like digital literacy gaps, gender disparities in technology adoption, and the effect of international regulations, particularly those related to deforestation and trade.
- SSA and South Asia, with their large proportion of smallholder farms, require AI-enabled solutions tailored to their specific needs. Issues of connectivity, affordability, data quality, and the potential for bias in data and algorithms also need to be addressed.
- Effective AI governance requires a collaborative and multi-stakeholder approach. Governments, NGOs, agritech startups, international organisations, and local communities must work together to develop and implement inclusive and sustainable AI-enabled solutions.
- Capacity building is vital, as shown in the Latin American context. It requires investment in digital literacy and technical training for farmers and other stakeholders. These efforts empower individuals to use AI technologies effectively. They also help ensure the digital divide does not deepen existing inequalities.

Reflection on SDG

The persistent digital divide, reinforced by cultural norms and limited female participation, hinders progress towards SDG 5 (Gender Equality) and SDG 10 (Reduced Inequalities). A lack of digital literacy data creates a major research gap. It also risks excluding vulnerable populations, undermining SDG 4 (Quality Education).

Initiatives such as SciCrop and Farmer.Chat improve digital accessibility. However, broader strategies are needed to ensure equitable access, which is vital for SDG 9 (Industry, Innovation, and Infrastructure).

AI bias poses another threat, as it risks deepening existing inequalities and directly contradicting SDG 10. National frameworks often prioritise AI development over equity. This neglects the specific needs of smallholder communities and slows progress towards SDG 1 (No Poverty) and SDG 2 (Zero Hunger). The absence of sector-specific agricultural AI governance frameworks makes these problems worse.

3. Reflection on findings and opportunities

This section primarily focuses on findings that aim to explore challenges, recommendations, opportunities, and future trajectories of AI-enabled solutions. This provides an analysis of emerging trends.

Horizon mapping in the context of agricultural AI considers broader socio-economic and environmental factors influencing agriculture. By leveraging foresight and trajectories, stakeholders can envision multiple scenarios and prepare for various possible outcomes. This ensures that AI-driven innovations contribute positively to the sustainability, productivity, and food security of global agricultural systems.

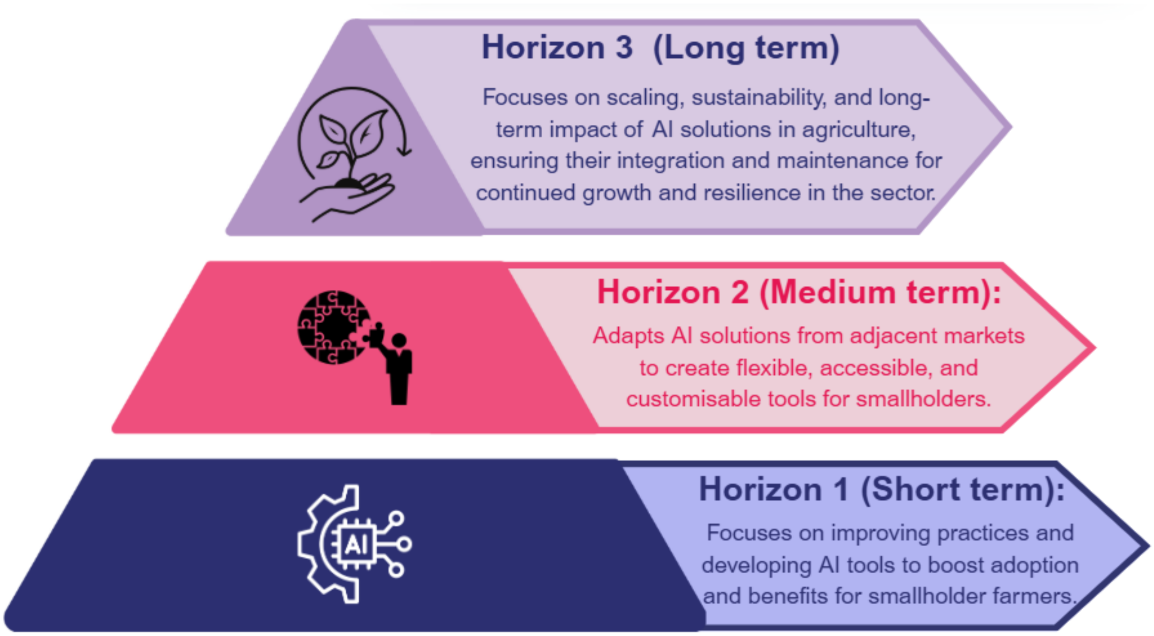
This study identifies three horizons for examining how AI may integrate into agriculture, with a particular focus on smallholder farmers in L&MICs (Wilcot 2022).

- **Horizon 1:** Short-term (one to three years): This horizon focuses on enhancing current practices and core activities. In the context of this report, short-term recommendations are based on the design and development of tools aimed at improving adoption and maximising the benefits for smallholder farmers.

- **Horizon 2:** Medium-term (two to five years): This horizon explores solutions borrowed and adapted from adjacent markets. It focuses on the accessibility and implementation of these AI-enabled solutions when tailored to the needs of smallholder farmers. Recognising that one size does not fit all, the emphasis is on developing flexible, accessible, and easy-to-use solutions. These can be customised to suit the diverse contexts of smallholders in different regions, minimising their challenges.

- **Horizon 3:** Long-term (five to twelve years): This horizon covers solutions that deliver incremental progress towards a desired future. It focuses on the scaling, sustainability, and long-term impact of AI-enabled solutions in agriculture. It seeks to ensure that these innovations can be effectively integrated and maintained for continued growth and resilience in the sector.

Figure 7: The three Horizons in the context of AI in Agriculture



3.1 Current challenges and best practices

AI integration in agriculture holds great promise but faces complex challenges that limit its adoption and impact, particularly for smallholder farmers.

- The fundamental disparity between agriculture's slow innovation cycle, which relies on two-season validations, and AI's rapid development creates a significant adoption gap. Stakeholders stated that this temporal mismatch alone is a substantial barrier to seamless integration.
- From the smallholder's perspective, several factors increase their vulnerability. Persistent intermediaries block direct market access. Limited logistical support in post-harvest phases, compounded by weak government extension services, creates further barriers. Moreover, digital accessibility and inclusion, especially in the context of advanced technologies, remain significant hurdles.
- Startups and developers encounter their own set of obstacles. Limited funding impedes their transition from short-term pilots to sustainable, long-term solutions. This prevents startups from reaching smallholder farmers at scale.
- A tech-centric background often limits developers' ability to fully grasp the nuances of farm-level problems. Stakeholders suggest a critical shift towards farmer-centric design, with solutions tailored to simplify farmers' lives rather than increase complexity.
- Governance frameworks currently lack specific measures for AI adoption in agriculture and risks the exclusion of smallholders and minority groups. The focus on adoption, rather than ethical development and usage, and the insufficient consideration of user rights, highlights a critical gap.

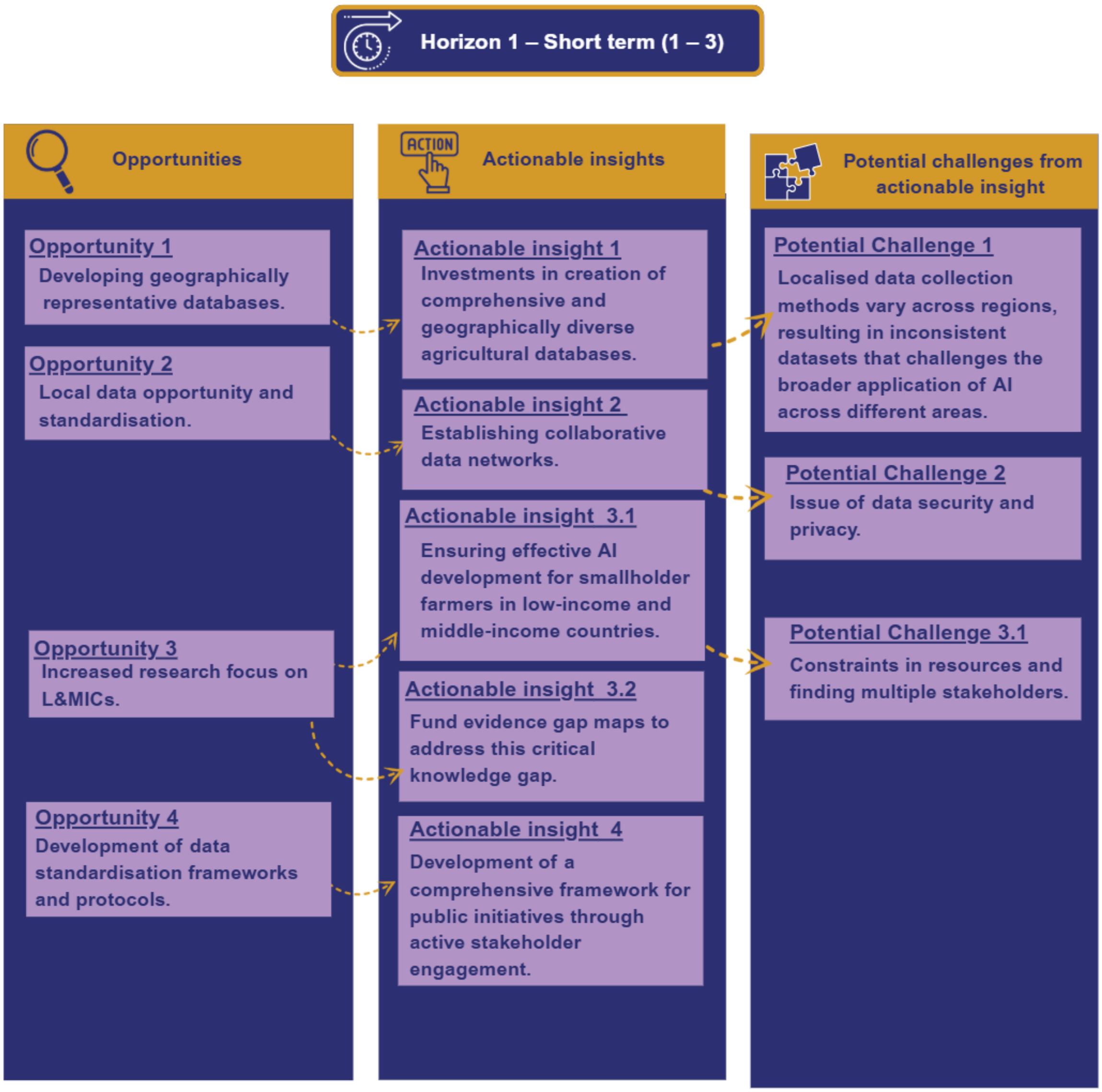
- Comprehensive and enforceable governance strategies are needed urgently to keep up with the rapid pace of AI innovation. This includes revising older agricultural policies to cover conditions and societal issues specific to the design and use of digital solutions as well.
- Challenges related to data collection, traceability, and the exacerbation of transparency problems. This is especially an issue in a highly context-specific (in terms of soil, climate and weather patterns, crop and livestock production systems, and socio-cultural practices) sector such as agriculture.
- Without geographic traceability, it is impossible to assess whether datasets are representative of the diverse agricultural landscapes where the use of AI is intended. This also makes it hard to prove the effectiveness of specific solutions to farmers.
- A key issue lies in the difficulty of acquiring reliable, consistent local data. This is compounded by several factors such as varying data standards across different databases, a lack of trust between national and private data sources, and the sheer cost of collecting localised information.
- Regional differences, ranging from cultural barriers to varied soil and weather patterns, necessitate specific data sets, making it difficult to create universally applicable AI-enabled solutions. In some cases, necessary data—such as historical weather and climate records or crop production data from national surveys—do exist. However, these data are often inaccessible. This lack of access hinders the development of accurate and effective AI applications (stakeholder workshop 1).
- The effectiveness of AI in agriculture remains poorly measured, particularly regarding its impact on productivity, food security, income, and livelihoods. Such measurements serve two purposes: they evaluate AI performance and they build trust and adoption among smallholder farmers. The first enables donors, funders, developers, and implementers to make evidence-based strategic decisions. The second allows farmers and other potential users of AI-enabled solutions to make informed choices about which technologies and services best suit their needs, context, and resources.
- There are challenges to scaling AI-enabled solutions in the field. While capacity-building and institutionalisation efforts are strong, scaling requires more context-specific and multi-dimensional approaches.
- The evidence fails to clearly define how funders, developers, and implementers contribute to scaling AI and ensuring it is accessible to smallholder farmers.
- The adoption and implementation of AI-enabled solutions in the field are iterative processes and require constant adaptation and feedback.

  In the case of Saagu Baagu, implementation partners like Digital Green had to maintain close contact with farmers through CRPs to address concerns and build trust. This underscores the need for ongoing engagement and a clear understanding of farmers' needs to bridge the adoption gap and support AI integration in agriculture.

The following section elaborates on opportunities for using AI in agriculture across the three horizons. Each opportunity draws on actionable insights from the study.

3.2 Horizon 1 – short term (one to three years)

Figure 8: Opportunities, actionable insights, and potential challenges in the short term



Opportunity 1: Developing geographically representative databases

While developers and researchers currently utilise plant and farm images from sources like PlantVillage Datasets, ImageNet, and IPI02 as seen in Section 4, it is often impossible to trace the origin of these images.

A key short-term opportunity lies in developing geographically representative databases. This action is also crucial for developing geographically centred AI-enabled solutions in agriculture.

Actionable insight 1: Investments in the creation of comprehensive and geographically diverse agricultural databases

Since gathering data is an expensive endeavour, it requires assistance from funding organisations or pooled government resources. This ensures that AI models are trained on data that are relevant to diverse target populations and farm production systems, thereby making the use of AI in agriculture more context-driven. To address the traceability issues outlined in the challenges, these **datasets must be structured by country and crop production cycles.**

Potential challenges emerging from actionable insight 1

Local data are essential for effective AI in agriculture. However, localised data collection poses challenges as discussed in section 3 page 44.

Opportunity 2: Local data opportunity and standardisation

As an extension to recommendation 1, it is important to recognise the critical role of local data in driving initiatives to improve data accessibility and standardisation. There's a growing potential to unlock valuable datasets currently held in private or less accessible repositories. (Stakeholder Session 1).

Actionable insight 2: Establishing collaborative data networks

The research recommends creating secure, collaborative platforms for sharing agricultural data (FAO 2024) (Dhulipala et al. 2023). These platforms can enable local organisations (for example, governments, businesses, and research institutions) to pool and access essential farm data. This includes disease incidence, visual records of pests and diseases, and weather patterns. They are categorised by countries, farm sizes and incomes, and farm cycle, to facilitate improved research and decision-making.

Establishing collaborative data networks can foster necessary collaboration and integration among various stakeholders (Ramanathan 2025). Geographically representative databases will help in creating farmer-centric solutions. Moreover, data on farm sizes and (potentially) incomes will contribute to developing products and research tailored to smallholder settings.

Potential challenges emerging from actionable insight 2

One of the key challenges that could potentially emerge is the issue of data security and privacy. This will be addressed under horizon 2.

Opportunity 3: Increased research focus on L&MICs

An extension of Opportunity 2 is a stronger research focus on L&MICs. This is crucial in the context of climate change and rising food insecurity, where smallholders in L&MICs face greater risks than those in high-income countries or on larger farms. Geographically representative databases and rigorous effectiveness measures can strengthen the relevance and validity of findings.

Actionable insight 3.1: Ensuring effective AI development for smallholder farmers in low- and middle-income countries

To ensure that AI development effectively serves smallholder farmers in L&MICs, particularly in LICs, a multifaceted approach is required. In recognition of the paucity of evidence regarding AI adoption bottlenecks in LICs, this study recommends prioritising research that places smallholder farmers at the centre of innovation.

This necessitates a shift in research practices. Firstly, AI development research, whether conducted by academic institutions, NGOs, or startups, must embrace interdisciplinary collaboration. This study highlights the need to integrate diverse academic fields and perspectives. In academic settings, this means forming interdisciplinary teams. Faculties such as agriculture and humanities work together to provide insights that cover agricultural, economic, and socio-cultural dimensions.

Secondly, to ensure that AI-enabled solutions are inclusive and relevant, design teams must be diverse. Incorporating agronomists, agricultural product development experts, and specialists in gender, culture, and social dynamics is crucial. This ensures that solutions are tailored to the unique needs of smallholders.

Finally, our findings emphasise the value of bundled AI-enabled solutions for smallholders. Therefore, we recommend mapping AI development solutions across the entire agricultural value chain. This strategic exercise will effectively pinpoint and address specific challenges, maximising the positive impact of AI interventions for vulnerable farming communities.

Potential challenges emerging from actionable insight 3.1
One of the main challenges lies in limited resources and the need to engage multiple stakeholders. One way to address this is to explore further in Horizon 2. Another widely recognised challenge with interdisciplinary and multistakeholder processes is that they are not only financially resource-hungry but also time-consuming. Strong facilitation and backstopping are required to foster relationships and mutual understanding, and reduce power and hierarchy structures (Sartas et al. 2019).

Actionable insight 4:

To address this, we recommend developing standardised operational definitions for these variables. This will ensure greater consistency and comparability in future research.

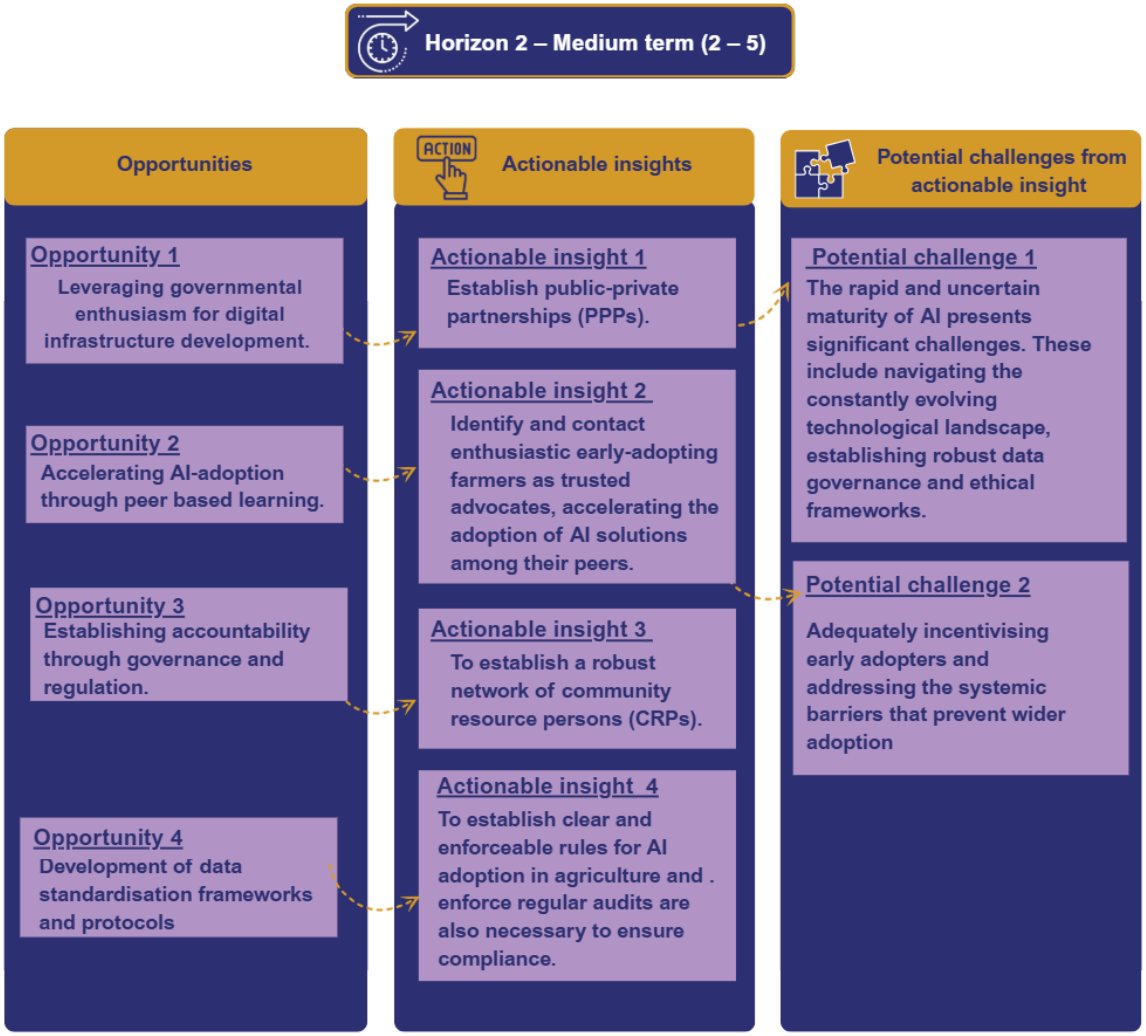
Box 5: Tailoring AI-enabled solutions for agriculture

During the development of AI-enabled solutions in agriculture, it is important to consider the following:

- Tailoring solutions to the specific needs and context of smallholders is essential. For example, providing a chatbot in the regional language (e.g., Telugu), and utilising video formats can improve accessibility and reach.
- Localisation is also vital; not only in terms of language but also in understanding nuances. For example, regional differences in how crops like maize are named can reveal variations, such as the terms used for hybrid maize varieties. Recognising these differences makes the solution more suitable for the target market.
- Moreover, it is important to develop holistic, bundled solutions that provide end-to-end solutions across the value chain.

3.3 Horizon 2 – short term (two to five years)

Figure 9: Opportunities, actionable insights, and potential challenges in the medium term



Opportunity 1: Leveraging governmental enthusiasm for digital infrastructure development

Governments should be involved in establishing infrastructure through multi-stakeholder projects. It is important to leverage governmental enthusiasm to take big risks to build digital infrastructures, frameworks, and encourage developers.

Actionable insight 1: Establish PPPs

By actively engaging diverse stakeholders, leveraging existing favourable conditions, and fostering sustained government enthusiasm. This collaborative approach will build the capacity and infrastructure needed to support AI-enabled solutions in agriculture.

Potential challenges emerging from actionable insight 1

While PPPs offer a promising avenue for building vital AI infrastructure, the rapid and uncertain maturity of AI presents significant challenges. These include navigating the constantly evolving technological landscape, establishing robust data governance and ethical frameworks, addressing critical skill gaps, ensuring long-term maintenance and sustainability, and the effective management of risks that are inherently associated with such complex systems. Successful PPPs must be adaptable and should proactively address these challenges to ensure the development of responsible and beneficial AI infrastructure.

Opportunity 2: **Accelerating AI-adoption through peer-based learning**

In the medium run, there is a real opportunity in fostering the adoption of AI-enabled solutions by smallholders through peer-based learning. Our study identified that smallholder farmers are more likely to adopt AI-enabled solutions when they see practical examples and hear from trusted peers. While financial incentives like subsidies may play a role, it is important to prioritise the establishment of robust peer-to-peer and farmer-to-farmer learning programmes. These initiatives leverage the power of shared experience and build trust, and accelerate the adoption of digital agricultural solutions.

Actionable insight 2:

Smallholder farmers do not belong to a homogeneous adopter category. inconsequently, there are early adopters and late adopters of AI technologies on farms (Ayisi et al. 2022). In response, this research recommends that implementors identify and contact enthusiastic early-adopting farmers. These individuals can serve as powerful examples and trusted advocates, accelerating the adoption of AI-enabled solutions among their peers.

Another way to foster peer-to-peer learning with smallholder communities is through self-help groups (SHGs). In the healthcare sector, these groups help in creating social capital, which is "critical to successfully layer... interventions” (Nichols 2021). In the agriculture sector, SHGs are "groups of farmers with identified common objectives, tasks, group identities and neighborhood” (VFPCK 2014; Manage 2020). They have also been referred to in the case of the Kenyan Tulime Tuvune. They have been very beneficial in establishing microfinance initiatives, technical expertise, "resulting in increased productivity and income generation” (Farmer’s Pride International 2025).

Potential challenge emerging from actionable insight 2

While peer-to-peer learning through lead farmers holds promise, its success hinges on adequately incentivising these early adopters and addressing the systemic barriers that prevent wider adoption.

Opportunity 3: Continued evaluation on adoption

To ensure the efficacy of AI deployment in agricultural settings, a framework for continuous, iterative evaluation is essential. The framework should include systematic data collection and analysis to track adoption patterns among smallholder farmers. It should also identify barriers to technology uptake and address them. Finally, it must use robust feedback mechanisms to detect and mitigate unintended monitoring consequences.

Actionable insight 3:

Our key insight here is to establish a robust network of CRPs, as demonstrated by the Saagu Baagu case study. These individuals, with their direct access to smallholder farmers, are vital for communicating the benefits of digital agriculture products. They also provide support and motivation, ensuring sustainable adoption, and help in gathering data on adopters and non-adopters.

Opportunity 4: Establishing accountability through governance and regulation

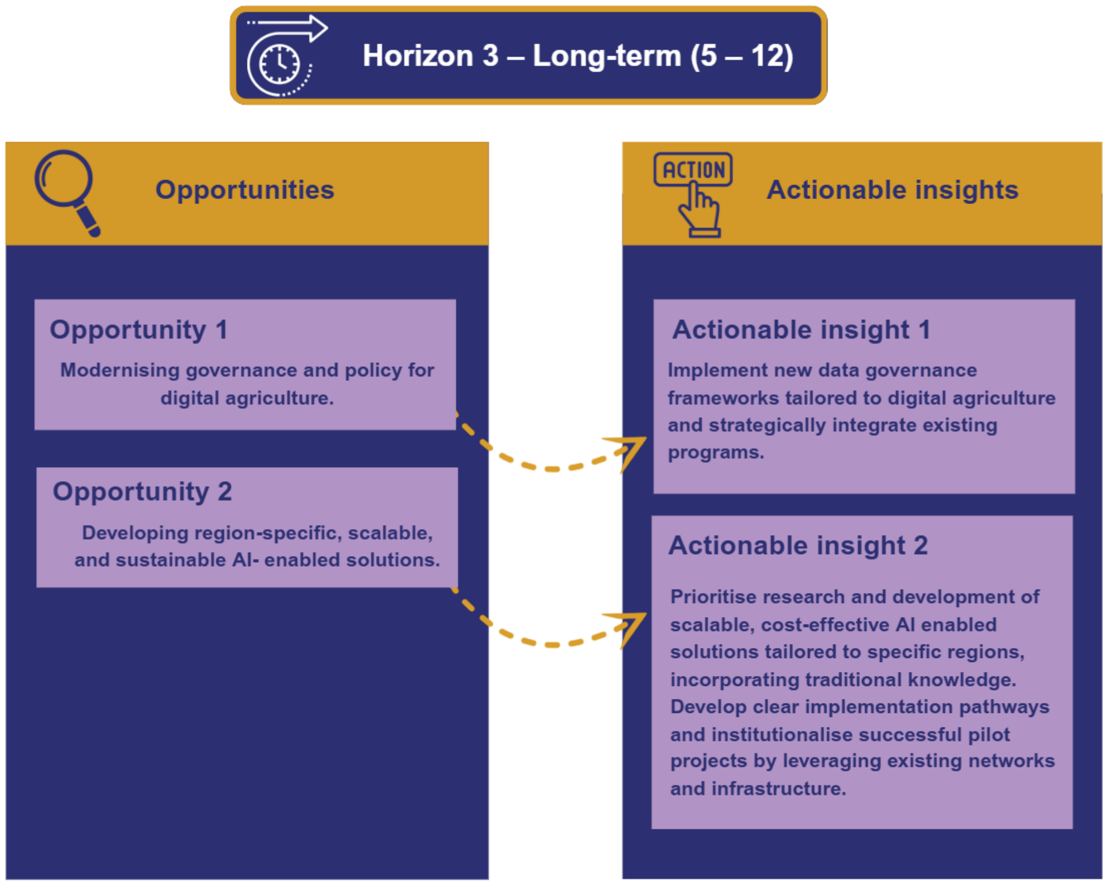
At the governance level, digital agriculture lacks clear accountability and redress processes – unlike traditional farming. Establishing these processes is essential, particularly to address data security and privacy concerns. While broad governance frameworks help translate AI ethics into practice, agriculture also requires sector-specific structures. **Actionable insight 4:**

From a regulatory perspective, it is critical to establish clear and enforceable rules for the adoption of AI in agriculture. These rules must ensure full transparency regarding the terms of service, data collection practices, and data access, for smallholders. Regular audits are also necessary to ensure compliance.

At the governance level, governments should establish dedicated departments for AI integration across sectors. For example, a mechanism similar to the Government Commissioner of Agriculture’s committee could set clear accountability parameters, address farmer grievances, and provide support. Such systems foster trust and encourage wider adoption.

3.4 Horizon 3 – long-term (five to twelve years)

Figure 10: Opportunities, actionable insights and potential challenges in the long term



Opportunity 1: Modernising governance and policy for digital agriculture

Governance and policy frameworks must be modernised to accommodate digital agricultural solutions. Existing agricultural policies are often inadequate for the complexities of these technologies. Therefore, the development of new data governance frameworks and the strategic integration of existing programmes like the Agriculture Infrastructure Fund are essential for creating a supportive ecosystem for digital agriculture.

Actionable insight 1

Implement new data governance frameworks tailored to digital agriculture and strategically integrate existing programmes, such as the Agriculture Infrastructure Fund, to create a supportive ecosystem. This will facilitate the development and deployment of innovative agricultural technologies even in the long term.

Opportunity 2: Developing region-specific, scalable, and sustainable AI-enabled solutions

This study highlighted the pivotal role played by region-specific solutions. Research should prioritise the design of scalable, cost-effective AI-enabled solutions with clear pathways for implementation in real-world contexts. Additionally, integrating traditional and community-driven knowledge into AI tools offers a unique advantage. Sustainability is also paramount, and it requires the institutionalisation of successful pilot projects to ensure continuity across leadership changes.

Actionable insight 2

Prioritise research and development of scalable, cost-effective AI-enabled solutions that incorporate traditional knowledge, and are region-specific. Develop clear implementation pathways and institutionalise successful pilot projects by leveraging existing networks and infrastructure, such as connecting agritechs with farmer organisations and cooperatives. Explore the creation of agricultural data exchanges and sandboxes for innovation.

Sustainability is paramount in this endeavour. Technologies must be institutionalised to maintain momentum despite shifts in leadership and government priorities. Saagu Baagu leveraged existing networks and infrastructure, such as linking agritech providers with farmer organisations and cooperatives like the National Bank for Agriculture and Rural Development (NABARD). This represented low-hanging fruit for rapid expansion. The model can scale further by adding new crops, creating an agricultural data exchange, and developing a sandbox for innovation. WEF representatives emphasise that while a comprehensive framework is essential, PPPs can advance through multiple entry points, including policy reforms, integration with existing programmes, and targeted use cases.

The importance of scalability cannot be overstated. With limited potential for expanding agricultural land, the majority of increased production must come from intensifying current methods. AI offers a powerful tool for optimising resources, improving yields, and ensuring sustainable practices, as highlighted (Khandelwal and Chavhan 2019). This is particularly vital in addressing the tension between high energy inputs and the growing demand for high-quality food.

Reflection on SDGs

The limited logistical support for smallholder farmers directly impacts SDG 2 (Zero Hunger) and SDG 1 (No Poverty) because it hinders access to essential resources and technologies. The lack of research and development funding, coupled with a lack of sectoral governance frameworks, impedes progress towards SDG 9 (Industry, Innovation and Infrastructure) and SDG 17 (Partnerships for the Goals). The lack of compliance in regulatory frameworks and the difficulty of tracing dataset origins raise concerns about transparency and accountability, both crucial for SDG 16 (Peace, Justice and Strong Institutions). Challenges in acquiring reliable and consistent local data and the lack of formal and standardised effectiveness measurements for AI tools hinder evidence-based decision-making, impacting all SDGs, particularly those related to food security and poverty reduction.

To address these challenges, this study proposes a phased approach. In the short run, creating geographically representative databases, shareable data platforms, and standardised effectiveness measurements will contribute to SDG 9 and SDG 17. Increased research focus on L&MICs and multi-stakeholder framework development will ensure inclusivity and relevance, supporting SDG 10 (Reduced Inequalities). In the medium run, inclusive collaboration, peer-to-peer learning through SHGs and CRPs, and robust monitoring and evaluation will enhance AI adoption and ensure accountability. This impacts SDG 1 (No Poverty) and SDG 2 (Zero Hunger). Establishing compliance frameworks will further strengthen SDG 16. In the long run, scaling and sustainable efforts will ensure the lasting impact of AI in agriculture, contributing to a wide range of SDGs.

By addressing these challenges and implementing the recommended strategies, the agricultural sector can leverage AI to create a more equitable, sustainable, and resilient agricultural sector. Ultimately this will contribute to the achievement of the 2030 Agenda for Sustainable Development**.**

4. Conclusion and recommendations

Long-term success depends on localising solutions, prioritising community values, embedding traditional knowledge, and building capacity to support uptake. This section addresses the imperative to mitigate unforeseen outcomes through responsible development and deployment strategies. Accordingly, this research presents recommendations for a broad range of stakeholders, from AI developers to policymakers. These recommendations seek to foster accountability, transparency, and trust in the proliferation of these systems.

Figure 11: Recommendations from the study

Future research

Recommendation 1: Increased landscaping on allied services

As noted in Section 2 and reiterated in Section 3, increase landscape analysis of AI-enabled solutions in other agricultural domains, such as livestock management, aquaculture, and unexplored areas.

Research 2: Increased focus on L&MIC research

As noted in Opportunity 3**,** the populations in these countries are disproportionately affected by agricultural challenges but remain underrepresented in AI research. This raises concerns about the applicability and effectiveness of AI-enabled solutions, and reveals a critical gap that needs to be addressed.

Recommendation 3: Conduct follow up rigorous evidence synthesis:

As mentioned above in Section 2, there is limited evidence on AI's effectiveness in smallholder settings. We recommend conducting rigorous follow-up evidence synthesis research, such as a systematic review or an evidence gap map, to strengthen the evidence base on AI's effectiveness for smallholders.

Recommendation 4: Developing a domain-based indicator framework for AI in agriculture
The framework should:

- Define key domains such as productivity, food security, income, and livelihoods.
- Recommend standard and context-specific indicators for each domain.
- Account for socio-technical factors, including farmers' practices, adoption, and comprehension.
- Encourage post-implementation audits to validate real-world effectiveness.
- Enable comparability of outcomes across geographies.

Organisational collaboration

Recommendation 5: Foster responsible AI practices:

As mentioned in Section 2.3, inclusivity is paramount for the ethical and effective implementation of AI in agriculture.

- Engage marginalised groups (smallholder farmers, women, rural communities) throughout the AI lifecycle to prevent exclusion and inequality.
- Move beyond development teams alone by embedding inclusivity in design, piloting, deployment and assessment.
- Replace tokenistic approaches (e.g., relying only on gender specialists) with genuine co-creation processes that integrate diverse perspectives.
- Conduct pilot testing with a wide range of users, including smallholder, mid-scale, and large-scale farmers, as well as forestry stakeholders to ensure contextual relevance.
- Establish mechanisms for ongoing stakeholder engagement to ensure AI-enabled solutions remain ethically responsible and responsive to community needs.

Recommendation 6: Building multi-stakeholder projects for the development and implementation of AI in agriculture

- Foster multi-stakeholder collaboration by encouraging partnerships among governments, charities, universities, tech companies, and global organisations.
- Establish government- and industry-led programmes and incentives to reward cross-sector collaboration in the development and deployment of agricultural AI-enabled solutions.
- Prioritise research and development of region-specific, scalable, and cost-effective AI tools with clear pathways for real-world implementation.
- Integrate traditional and community-driven knowledge into AI design to ensure contextual relevance and enhance adoption.

Farmer adaptation and bridging the digital divide

Recommendation 7: Infrastructure and connectivity gaps:

- Invest in rural connectivity to expand digital infrastructure for smallholder farmers.

- Enhance digital literacy programmes to improve farmers' capacity to engage with AI tools.
- Leverage accessible platforms, such as mobile applications (e.g., WhatsApp) and satellite technologies, to bridge access gaps.

Recommendation 8: Showcasing success stories and catalysing peer to peer learning

- Engage enthusiastic early adopters among smallholder farmers to serve as trusted advocates and accelerate AI adoption.Empower early adopters to showcase success stories and facilitate peer-to-peer learning within their communities.
- Integrate AI interventions into existing village-level institutions to leverage established trust and deliver multiple benefits.
- Apply layered intervention strategies, as demonstrated in the Saagu Baagu example, to enhance impact and adoption.
- Utilise SPC (Statistical Process Control) methods to monitor and optimise AI implementation.
- Balance depth and scale by combining personalised capacity-building ("touch and feel" learning for low-literacy groups) with broader CRP (community resource person) deployment.
- Develop sustainable funding models to support both intensive engagement and widespread adoption.

National and international governance

Recommendation 9: Prioritise supporting regulatory frameworks:

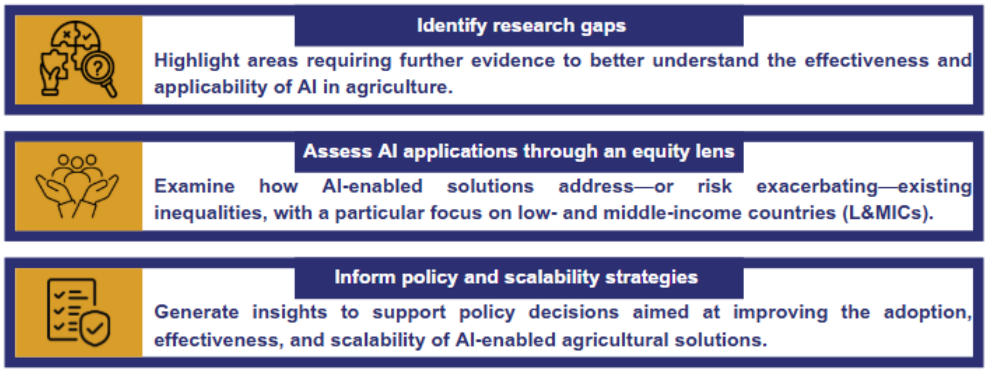
- Establish governance structures that enable the development of scalable AI-enabled models for agriculture.
- Develop transparent, farmer-centric, and demand-driven frameworks to promote trust and prevent unintended consequences.
- Align AI-specific and agriculture-sector policies at local, national, and regional levels to ensure coherence and effectiveness.
- Strengthen international regulatory frameworks such as those promoting traceability (e.g., EU Deforestation Regulation) to support responsible AI adoption in agriculture.

5

Annexure

5. Annexure

Figure 12: Core objectives of the study



While AI-enabled solutions hold significant potential for advancing agricultural outcomes, this study recognises that they are not a comprehensive solution to all sectoral challenges. The analysis offers a nuanced perspective on how AI applications can be contextually adapted to diverse agricultural needs. It aims to deliver practical insights for practitioners, policymakers, and other stakeholders.

This landscape study adopted a mixed-method approach, collecting both qualitative and quantitative data, which will together provide (1) an overview of the existing AI landscape in the agricultural sector, and (2) evidence on the effectiveness and impact of AI-enabled solutions. The mixed-method included a scoping review, an RR and a narrative review, regional and global deep dives, case studies, and stakeholder engagement.

Box 06 provides an overview of the research questions.

Box 6: Key research questions

1. **Defining AI:**
    - What are the major categories of AI-enabled solutions in agriculture?
    - What is the current stage of development of AI-enabled solutions and their deployment in the field?
    - What typology framework can be used to understand the types of AI applications in agriculture?
    - Who are the key vendors/institutes under each of these typologies?
2. **Understanding effectiveness of AI-enabled solutions:**
    - How effective are AI-enabled solutions in improving outcomes related to productivity?
    - How effective are AI-enabled solutions in improving outcomes related to food security?
    - How effective are AI-enabled solutions in improving income and livelihoods?

3. **Ethics and equity:**
    - What are the practical barriers for developing AI-enabled solutions for agriculture at scale, particularly at low-income settings?
    - How can AI-enabled solutions in agriculture be designed and implemented to maximise equity and avoid exacerbating existing inequalities?
4. **Horizon mapping:**
    - What are the recommendations for AI-enabled solutions in agriculture?
    - What are the (projected) medium-, short- and long-term trajectories of specific AI-enabled solutions?

Detailed explanation of methodologies

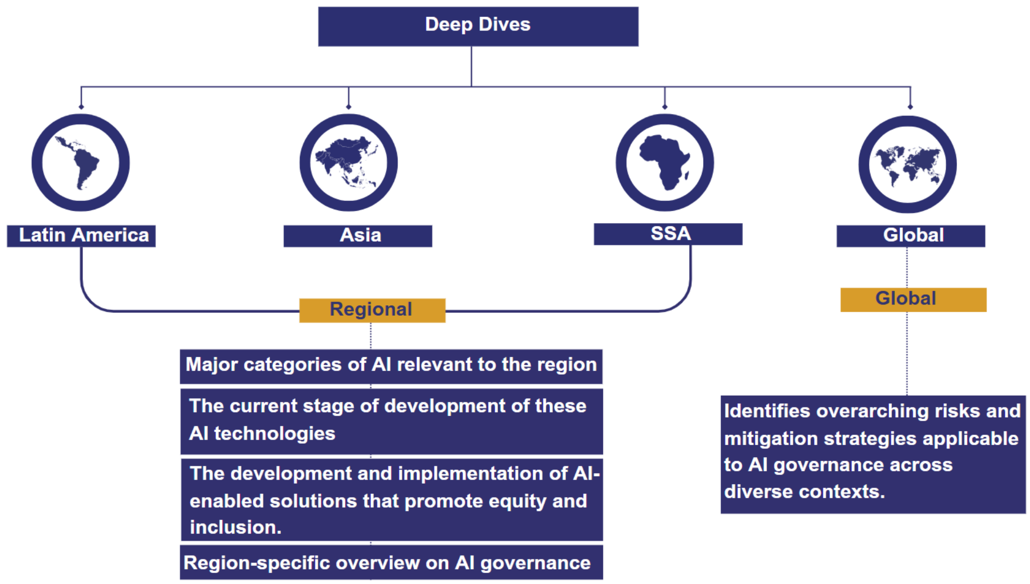
The methodological components of this study were designed to complement one another, ensuring a comprehensive, contextually grounded, policy-relevant analysis of AI-enabled solutions in agriculture. By integrating multiple approaches, the study addressed various dimensions of the research questions while enhancing the robustness and credibility of the findings.

As stated earlier, this document presents findings from all methodologies except the RR. The RR served as the evidence base, synthesising peer-reviewed literature on measurable outcomes in agricultural productivity, food security, and livelihoods. For the RR report, please refer to Rapid Review

The narrative review was conducted to complement the RR by incorporating grey literature, including non-peer-reviewed sources. This was particularly important for addressing emerging trends and perspectives from developers, implementers, and funders.

The deep dives provided region-specific insights into governance mechanisms, regulatory environments, and adoption challenges in Latin America, SSA, Asia, and beyond. These deep dives validated the broader trends identified in the literature reviews while highlighting contextual nuances that influence the implementation of AI-enabled solutions at the local level.

Figure 13: Deep dives overview

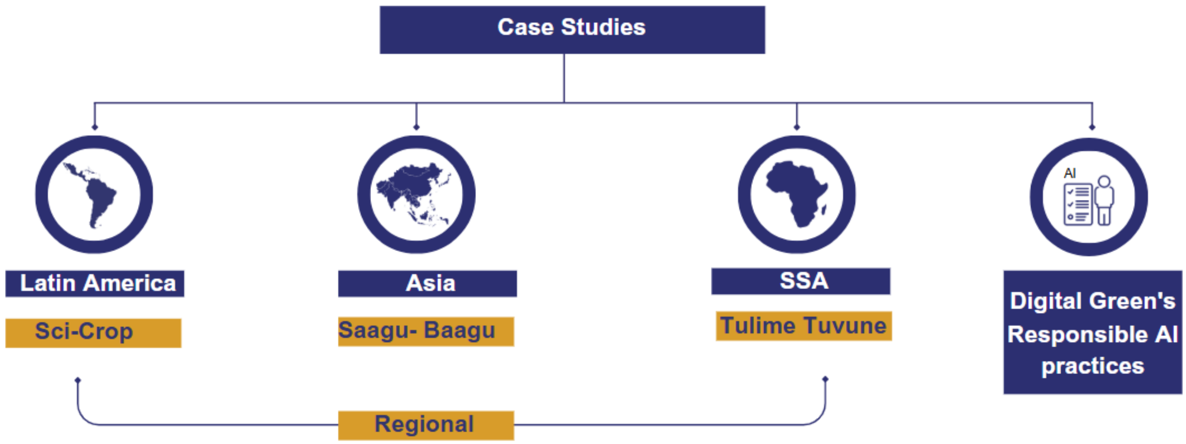


The structure of the deep dives was guided by a set of interconnected research questions designed to provide a comprehensive understanding of AI governance. Each regional deep dive (Latin America, SSA, and Asia) investigates (1) major categories of AI relevant to the region, (2) the current stage of development of these AI technologies, (3) the development and implementation of AI-enabled solutions that promote equity and inclusion, and (4) region-specific AI governance initiatives

Incorporating case studies within the methodology helped the research team capture key real-world examples of AI-enabled solutions designed for smallholders in L&MICs (Campbell 2015). The case studies focused on specific AI products, tools, and applications that are actively being developed or implemented to address challenges faced by smallholder farmers. As a qualitative method, case study research relies heavily on the researcher as the principal tool for data collection and analysis (Campbell 2015).

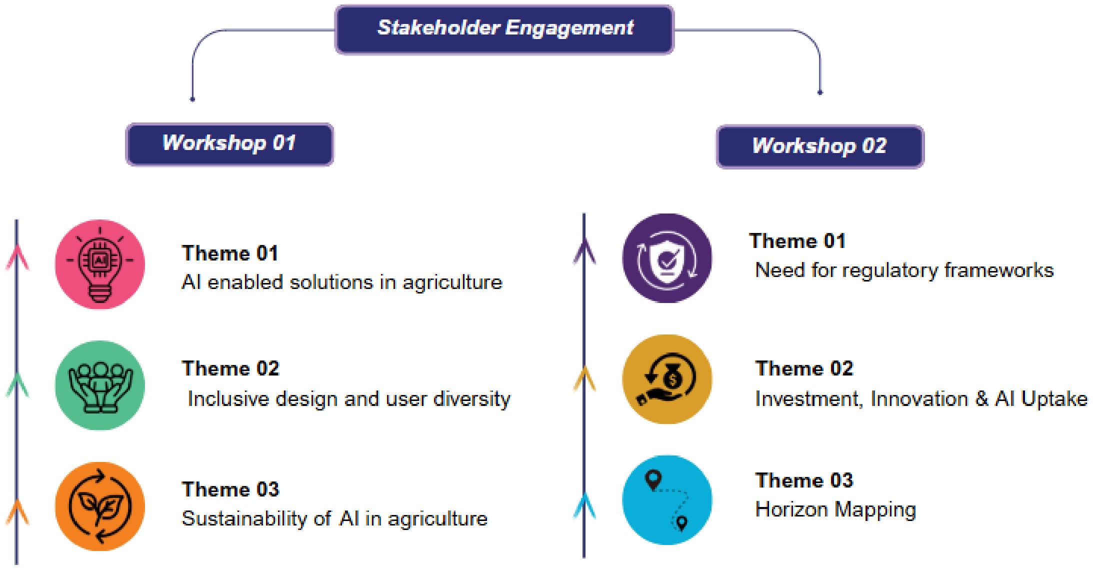
The case studies included in the landscape review offered practical examples of AI application. It focused on factors such as farmer perceptions in SSA, governance structures in Latin America, and large-scale AI deployments in Asia. These case studies enriched the analysis by illustrating how AI-enabled solutions operate in real-world settings, and underscoring the practical challenges and opportunities associated with their adoption.

Figure 14: Overview of case studies



To strengthen the study's findings, the research team held two stakeholder engagement (SE) sessions at key stages of the research process. These engagements validated emerging insights, identified evidence gaps, and ensured the study's relevance to practical and policy contexts. The research team identified thematic areas that aligned with the main research questions and targeted domains needing further investigation to strengthen and contextualise the findings. Figure 15 provides an overview of stakeholder workshops.

Figure 15: Overview of stakeholder engagement workshops



In sum, the interconnectedness of these methods provided a layered analysis that balances quantitative data with qualitative insights, global trends with local contexts, and theoretical frameworks with operational realities.

Figure 16: Mapping of research questions and methodologies

Research question	Methodologies
Research theme 01: Defining AI: How is AI defined in the agriculture sector?	
What are the major categories of AI-enabled solutions in agriculture?	RR, NR, CS, DD, SE
What is the current stage of development of AI-enabled solutions and their deployment in the field?	RR, NR, CS, DD, SE
What typology framework can be used to understand the types of AI applications in agriculture?	RR, NR, TD, SE
Who are the key vendors/institutes under each of these typologies?	RR, NR, TD, SE
Research theme 02: Understanding effectiveness	
How effective are AI-enabled solutions in improving outcomes related to productivity?	RR, CS, DD, SE
How effective are AI-enabled solutions in improving outcomes related to food security?	RR, CS, DD, SE
How effective are AI-enabled solutions in improving income and livelihoods?	RR, CS, DD, SE
Research Theme 03: Ethics and equity	
What are the practical barriers for developing AI-enabled solutions for agriculture at scale, particularly at low-income settings?	RR, NR, CS, DD, SE
How can AI enabled solutions in agriculture be designed and implemented to maximise equity and avoid exacerbating existing inequalities?	RR, NR, CS, DD, SE
Research theme 04: Horizon mapping	
What are the recommendations for AI-enabled solutions in agriculture?	RR, NR, CS, DD, SE
What can we say about medium, short, and long run trajectories of specific AI-enabled solutions?	RR, NR, CS, DD, SE

RR Rapid review · NR Narrative review · TD Typology development
CS Case study · DD Deep dives · SE Stakeholder engegment

Detailed limitations of each methodology

A key limitation of the narrative review is the inherent challenge posed by the lack of transparency in the reporting and conducting of narrative syntheses. However, this lack of prescriptive guidelines allowed the research team to relax some of the restrictions imposed by the RR methodology. The development of typologies relied on secondary data inputs from other methods used in the study. This came with the risk that these methods would not generate the type or quantity of data anticipated. Such data were necessary for developing both broad and in-depth insights into the agricultural AI landscape and its developments.

Case studies and deep dive methods are highly qualitative by design, and examine specific cases (e.g., a specific vendor or technological solution, a specific use context). This makes the findings primarily illustrative with limited generalisability. The methodological limitation is the reliance on thematic analysis, which has a degree of subjectivity and poses challenges to replicability (Roberts et al. 2019). While the limitations of the deep dive approach are acknowledged, the concentrated, region-specific findings have been systematically used to inform relevant policy recommendations.

Similarly, this research acknowledges that insights gathered through stakeholder engagements are subjective or context-specific in nature. However, these engagements were instrumental in providing a nuanced understanding of regional perspectives and in situating them within the global evidence base generated through other methodological components.

The research team intentionally leveraged the subjectivity of the methodological components to bolster the findings. These methods provided the researchers with the flexibility to explore different themes. These themes included innovation-related support, role of institutional or regulatory frameworks, digital divide, need for digital capacity building, and the role of gender and cultural components in supporting or hindering AI adoption. Overall, the mixed-methods approach helped contextualise gaps in individual methodologies, thereby addressing some of their inherent limitations.

Details on the current stage of development of AI-enabled solutions and their deployment in the field

In recent years, AI has permeated numerous industries, and agriculture is no exception (Dal Mas et al. 2023). Agricultural production systems that rely on traditional methods are increasingly facing challenges in meeting the rising global demand for agricultural products. To address these challenges, the sector is undergoing a cycle of change, known as Agriculture 4.0. This aims to enhance productivity, resource efficiency, and sustainability through the adoption of modern farming practices and technologies, including digital technologies. Within this reshaping, digitisation plays a foundational role by converting previously analogue data (e.g., paper logbooks) into digital formats, providing the essential data inputs for AI-enabled technologies to function effectively. Digitalisation, a broader process, builds on digitisation by integrating these digital technologies into agricultural systems to improve decision-making, optimise resource use, and drive sustainable outcomes (FAO 2022b). This has driven the strategic integration of AI in global agriculture (FAO 2022).

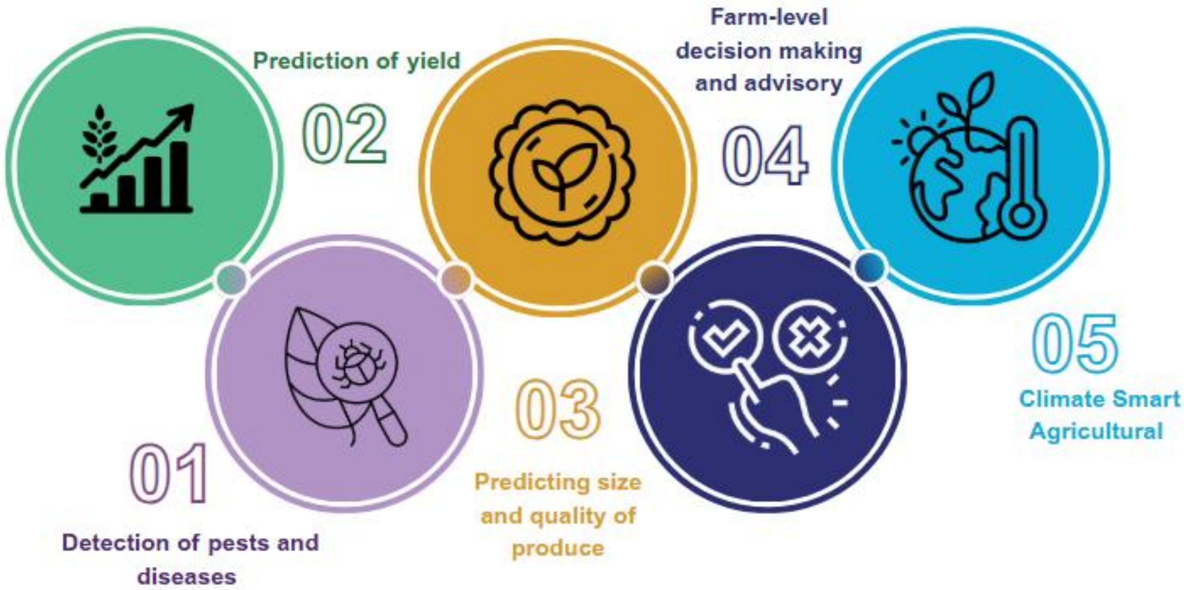
Farmers can upload plant images for diagnosis, and AI will identify issues and offer professional advice. This tool helps improve crop health, pest management, access to resources, and enhances productivity and sustainability.

Details on development and testing

In some cases, solutions are still undergoing technical refinement and are not yet ready for field testing. In others, there may be barriers preventing the transition from development to practical application, such as limited resources, regulatory hurdles, or insufficient stakeholder engagement. An alternative explanation is that the development of AI-enabled solutions for agriculture is yet to reach a stage suitable for widespread practical application. These scenarios provide an opportunity for targeted strategies to bridge the gap between development and widespread adoption. Moreover, stakeholder workshops highlighted a key challenge: the disconnect between the rapid pace of AI development and the comparatively slower, more deliberate nature of the agricultural sector. Stakeholders noted that transformation in farming is inherently gradual, and farmers are pragmatic adapters who exercise caution when integrating new technologies. Unlike other sectors where rapid trials and adjustments are common, farmers often need to assess the outcomes of an entire crop cycle before making informed decisions about changing established practices. This cautious approach, coupled with the rapid advancements of AI technologies, contributes to the slow adoption rate. Despite this, emerging solutions, particularly in crop production, demonstrate a promising sign of gradual progress.

Details on primary use cases of AI-enabled solutions

Figure 17: Primary use cases of AI-enabled solutions in agriculture



A primary application of AI in agriculture is pest and disease detection. The YOLO models in Côte d'Ivoire is a relevant example. They are used in cocoa plantations to classify cocoa pods, prevent disease spread, enhance overall crop yield, and improve bean quality by detecting diseases (Ferraris et al. 2023). Similarly, PlantVillage Nuru uses image recognition to help farmers identify diseases and pests in India, Kenya, and Tanzania (CGAIR 2020). Stakeholders mentioned that neuro-trained machine learning models are being employed for plant disease detection. Cassava production in Tanzania is a relevant example. This system uses cameras to monitor crops, optimise harvest timing, and detect plant diseases. Over five years of development, this AI-driven approach has improved crop management and disease control. Aerobotics (South Africa) uses AI-powered drones to analyse crop health, detect nutrient deficiencies, distribute beneficial insects, and map farm fields (Aerobotics 2025).

Another important use case is yield prediction, as demonstrated by a study that utilises IoT systems to predict yield in wolfberry plantations, a major crop in China's Ningxia province (Jin et al. 2020). Similarly, as an extension of yield production, some AI-enabled solutions help in predicting the size and quality of produce. In order to boost yields and profit, Hello Tractor, in collaboration with Atlas AI, is developing predictive AI and machine learning (ML) models for tractor utilisation (Hello Tractor 2019; Atlas AI 2024; Gwagwa et al. 2021). FreshPlaza uses AI and computerisation to assess the size and quality of produce in countries in Asia and

SSA (Bava 2023). IntelloLabs from Singapore uses AI-powered image recognition to assess agricultural produce quality, ensuring quality control and reducing food waste.

Farm-level decision-making and advisory services are another important use case of AI-enabled solutions in agriculture. The RR recommends the use of machine learning chatbots through which multiple stakeholders can converse with farmers (Mokaya 2019). Such chatbots are already in use. In India, organisations such as KissanAI are piloting generative AI chatbots for farm advisory services, using synthetic data to support early-stage research. Farm.Link, Agripredict, and Tulime Tuvune apply AI to optimise farm practices. Agribot (AGRA and Microsoft) provides AI-driven advice on farming, pest control, and market information (AGRA 2022). In Ghana, Esoko connects farmers with markets using AI (Esoko 2024).

Climate-smart agricultural solutions have become increasingly important due to growing concerns of climate change. Climate-smart technologies represent a broad portfolio of services that can be provided to farmers, including precision agricultural solutions such as the provision of improved crop varieties, soil management practices, and crop management practices. For further information, refer to the rapid review.

Table 1: Scicrop's client breakdowns by size.

Type of client	Number of clients	Products they use
Large-scale farming companies or related	67	InfinityStack, Farmgis, Pluvio, Webfarms
Small- to medium-sized farmers	40	Farmgis, Pluvio, Webfarms

Table 2: SciCrop's products.

Product	Description
FARMGIS	A dashboard that focuses on geographic analytics. It provides access to various maps, indexes, and geographic analyses by processing images from satellites and unmanned aerial vehicles.

PLUVIO	A dashboard that focuses on weather analytics. It gives farmers direct access to all types of climate analyses, including alerts, forecasts and monitoring through IoT sensors and satellite data.
WEBFARMS	A dashboard that focuses on farm data analytics. Farmers or farm companies can access all types of analyses including number of farmers, rural properties and the agricultural market. It covers everything from environmental data to productivity data.
InfinityStack	The first AI resource platform for agribusiness and the food industry in Brazil. It enables companies to: • Integrate all types of data related to their agricultural or food production. This includes climate data, satellite imagery, industry and field sensors, Enterprise Resource Planning (ERP) and Customer Relationship Management (CRM) data, machinery and tractor data, and market data. • Select relevant algorithms from a library of hundreds and generate insights from integrated data. These insights are tailored to specific business challenges, without requiring deep technical knowledge. Democratise the knowledge generated by the algorithms applied to integrated data through LLMs. This can be accessed by employees privately via WhatsApp, Teams, and Telegram without relying on third-party cloud models.

Box 7: Highlight: WEF’s AI4AI initiative

The WEF emerges as a pivotal international actor through its AI4AI initiative, which aims to drive digital agriculture adoption in Asia. By establishing a governance framework focused on digital public infrastructure, gender-inclusive agritech, and value chain transformation, the WEF facilitates PPPs in India, notably in collaboration with state governments like Telangana. This initiative, supported by funders such as the Gates Foundation, Yara India, Bayer Crop Science, and Bajaj, underscores the WEF's commitment to scaling agritech solutions. The WEF's report, *Agritech for Women Farmers*, highlights its focus on inclusive growth and the effectiveness of agritech for women farmers, drawing on case studies from diverse regions.

The AI4AI initiative is a framework established by the WEF. The main aim of this initiative is to scale up emerging digital technologies through PPPs. They aim to **reach** 1 million farmers by 2027 (WEF 2023b). Their primary objectives are:

- ***Inclusivity***: Empowering women and youth by providing them access to finance, insurance, and infrastructure.
- ***Efficiency***: Using IoT, AI, and Blockchain to enhance efficiency and reduce crop waste.
- ***Sustainability:*** Reducing agricultural footprint through precision agriculture by reducing crop waste, inputs, and building resilience.

They achieve these objectives by: “building digital public infrastructure, gender-inclusive agritech, and value chain transformation” (AI4AI 2024)

Box 8: Effectiveness in Saagu Baagu

The Asian case study about project Saagu Baagu presents a clear impact assessment policy, as seen in Figure 18. The productivity dimensions measured include improvement in yield, decrease in cost of cultivation, increase in farm revenue, profits/losses from sale produce and increase in household income. Digital Green, the implementation partner, conducted baseline and endline studies in the Khammam district to measure yield and productivity changes in selected and controlled plots. The project reached 17,800 farmers, whose improved yield resulted in an average increase of Rs 1,870 per 100 kg ($22.86/100kg) in sales compared to traditional practices **(WEF 2023b)**.

Figure 18: Demonstrated effectiveness

Quantitative impact

Economic impact

- Improvement in yield
- Decrease in cost of cultivation
- Increase in revenue (farm-gate price)
- Profit/loss from sale of produce
- Increase in net household income

According to insights from stakeholder engagement, the impact of the AI solution in the Saagu Baagu project was measured using several key metrics. These metrics included productivity, cost savings, and income changes for farmers at the community level. At the farm level, the focus was on efficiency gains, such as cost per farmer and cost per adoption. The Saagu Baagu team did not conduct the evaluation themselves. It was carried out by the Abdul Latif Jameel Poverty Action Lab (J-PAL). The evaluation involved a wide range of stakeholders. This included government organisations like the Department of Horticulture in Telangana, agritech startups like Kalgudi, KrishiTantra, and AgNext, and farmer-producer organisations on the ground. The results highlighted significant improvements in both the community of farmers and the broader ecosystem. They demonstrated that AI tools successfully connected farmers with the services they needed, leading to cost reductions and increased income.

Box 9: Measuring effectiveness from a digital AG perspective

Developed by Safaricom, a major telecommunications company in Kenya, in partnership with iProcure and Arifu, DigiFarm aims to provide easy access to services like quality farm inputs, credit and insurance, and customised information on farming best practices. Although not an AI enabled solution, the experience of DigiFarm highlights the importance of user adoption in effective agritech. It is an agritech mobile platform designed for smallholder farmers. In theory, DigiFarm helps agribusinesses and farmers share information and conduct transactions through its integrated platform (CGIAR 2022).

However, despite having over 1 million registered users, the active user rate of the platform is low. Estimates suggest that less than 24 percent of users engage with the platform regularly.

There is no conclusive evidence explaining only one quarter of registered users actively use DigiFarm. This could be due to the platform not meeting users' needs in its UX design, or perhaps the link to quality farming inputs is not as smooth as expected. It is also possible that many of the registered users are unable to access the data that are needed to run the platform.

DigiFarm can serve as an example of how and why agritech solutions must be evaluated within their context. This involves assessing the socio-technical nature of the solution itself, the evidence of its effectiveness, and its ability to meet the needs of stated user groups.

Table 3: Key insights on gaps in governance across region

Overview/Region Bloc	Latin America & Caribbean	Sub- Saharan Africa	Asia
Governance frameworks	***Multistakeholder governance*** AI governance requires coordination between governments, NGOs, and other stakeholders. Examples include *AgroTIC 2024* in Colombia and partnerships in Barbados.	***Potential risks*** Existing AI governance frameworks do not adequately capture potential economic inequalities, social inequalities, or AI-related risks.	***Absence of sectoral governance*** The clear absence of agricultural sector governance standards risks leaving smallholders out of the equation.
Regulatory frameworks	***National & sectoral AI regulation***	***Inequality gaps***	***Inequality gaps***

	Effective governance requires both AI and sectoral regulation. ***International regulation*** International regulations like the EU deforestation act demonstrate the need for robust regulatory sectoral frameworks.	Little attention is given to the social and economic risks of AI for underserved groups, including smallholder farmers, women, and youth.	Lack of clear focus on marginalised communities like smallholders, and women. ***Lack of enforcement mechanisms*** All the governance frameworks are voluntary, with no compliance mechanisms in place.
Building infrastructure	***Women entrepreneurship*** There is a significant opportunity within the AgriTech space. ***Capacity building*** This is a prerequisite for ensuring the adoption and effective use of AI.	***Integrated farmer - centric approach*** Building strong data and technology infrastructure that balances innovation and environmental transitions while upholding ethical standards.	**N/A**

Table 4: Ethical AI principles, challenges, and potential solutions in agriculture

AI principle and definition	Challenges in agriculture	Potential solutions in agriculture
Fairness Ensuring AI systems do not discriminate, and provide equitable outcomes across diverse populations.	Risk of AI favouring large-scale farms due to biased data. Disadvantaging smallholders with less data representation.	Crop yield prediction models accommodate diverse soil types and climates, making them accessible to farmers across different geographic regions**.**
Transparency Making AI algorithms and decisions understandable and accessible to stakeholders.	Complex AI systems may be difficult for farmers to interpret. This can lead to mistrust, or misuse of the technology.	AI-driven irrigation decisions are paired with explanations of how water use is optimised.
Accountability Assigning responsibility for AI outcomes, including errors or harms.	Determining liability when AI errors lead to significant crop damage or financial losses can be contentious.	Farmers are notified and compensated if an AI pest-control system misidentifies crop pests.
Privacy Safeguarding personal and sensitive data used in AI systems.	Potential misuse of sensitive farm data by third parties, or competitive exploitation.	Safeguarding farm-level GPS data used to optimise planting patterns against unauthorised access.
Safety Ensuring AI systems do not pose harm to humans,	AI-driven equipment malfunctions can cause accidents, putting workers and livestock at risk.	AI-controlled machinery must be programmed with fail-safes to avoid harming workers in fields.

animals, or the environment.		
Sustainability Designing AI to minimise environmental impact and promote long-term ecological balance.	AI may prioritise efficiency over long-term soil health, leading to unsustainable farming practices.	AI tools optimise fertiliser application, minimising runoff and safeguarding waterways.
Inclusivity Engaging diverse stakeholders in the design and deployment of AI systems.	Exclusion of marginalised communities in AI design due to lack of representation or digital infrastructure gaps.	Co-creating AI tools with inputs from smallholder farmers to meet their specific needs.
Autonomy Supporting user independence in decision-making without undue reliance on AI.	Over-reliance on AI could erode farmers' traditional knowledge and decision-making skills.	Farmers can override AI crop rotation suggestions if local conditions warrant it.

Table 5: List of studies included in the narrative review

S. no	Authors	Title
1	IDRC 2024	A Project on Predicting Drought in Cuba | IDRC - International Development Research Centre
2	Jelinek 2022	Advancing Smallholder Agribusiness in Botswana Through Smart Digital Innovation

3	Ampatzidis 2022	Artificial Intelligence (AI) for Crop Yield Forecasting
4	UNDP 2024	Agricultural Transition Using the Internet of Things and Artificial Intelligence
5	Zhang 2024	AI, Sensors, and Robotics for Smart Agriculture.
6	Dixit 2024	AI, the New Wingman of Development
7	Owino 2023	Challenges of Computer Vision Adoption in the Kenyan Agricultural Sector and How to Solve Them: A General Perspective.
8	IDRC 2025	Creating Transformational Impact: Lacuna Fund Enables Local AI solutions by Filling Data Gaps in Africa | IDRC - International Development Research Centre
9	Yasabu 2019	Digitalizing African Agriculture: Paving the Way to Africa's Progress Through Transforming the Agriculture Sector
10	Zhang 2024	Editorial: Artificial intelligence and Internet of Things for Smart Agriculture
11	Zhang 2023	Editorial: Machine Learning and Artificial Intelligence for Smart Agriculture. | EBSCOhost
12	FAO 2024	Digital Agriculture in FAO Projects in Sub-Saharan Africa
13	Hossain (2022)	Use of Artificial Intelligence for Precision Agriculture in Bangladesh

14	IDRC 2023	How Agripoa is Using AI to Empower Tanzanian Poultry Farmers | IDRC - International Development Research Centre
15	Kulykovets (2023)	Automation of Production Processes in Agriculture Using Selected Artificial Intelligence Tools
16	Gupta 2023	Management of Agriculture Through Artificial Intelligence in Adverse Climatic Conditions.
17	Sparrow 2021	Managing the Risks of Artificial Intelligence in Agriculture
18	Jpal 2022	Phone-Based Technology for Agricultural Information Delivery
19	Priya (2020)	ML Based Sustainable Precision Agriculture: A Future Generation Perspective
20	Qiao (2022)	Editorial: AI, Sensors and Robotics in Plant Phenotyping and Precision Agriculture
21	Qiao (2022)	Editorial: AI, Sensors and Robotics in Plant Phenotyping and Precision Agriculture
22	Rozenstein (2024)	Data-Driven Agriculture and Sustainable Farming: Friends or Foes?
23	Sheikh (2021)	IoT and AI in Precision Agriculture: Designing Smart System to Support Illiterate Farmers
24	CGIR 2023	Three Ways that Machine Learning Can Bring Precision Agriculture to Small-Scale Farms
25	Son 2024	Towards Artificial Intelligence Applications in Precision and Sustainable Agriculture.

26	Zhang (2024)	Editorial: Artificial intelligence and Internet of Things for Smart Agriculture.
27	Zhang (2024)	Achieving the Rewards of Smart Agriculture.

Table 6: Description on funding information from studies included in the narrative review

S.no.	Authors	Title	Funding
1	Jelinek 2022	Advancing Smallholder Agribusiness in Botswana Through Smart Digital Innovation	IDRC
2	Ampatzidis 2022	AE571/AE571: Artificial Intelligence (AI) for Crop Yield Forecasting	ITU
3	Zhang 2024	AI, Sensors, and Robotics for Smart Agriculture. | EBSCOhost	International Development Research Centre (IDRC) and the Swedish International Development Cooperation Agency (SIDA)
4	Dixit 2024	AI, The New Wingman of Development	World Bank
5	Zhang 2024	Editorial: Artificial intelligence and Internet of Things for Smart Agriculture. | EBSCOhost	Bill & Melinda Gates Foundation Projects, Taking Maize Agronomy to Scale in Africa (TAMASA), The

			Mastercard Foundation and the World Bank.
6	Hossain (2022)	Use of Artificial Intelligence for Precision Agriculture in Bangladesh	Funding partners of digital activities are generally the well-known bilateral or multilateral institutions that support agriculture development (including the UN System, the African Development Bank, the EU, the Foreign, Commonwealth and Development Office, and the International Fund for Agricultural Development). In most cases, their support went to broader agrifood projects rather than digital activities. The most frequently cited funding partners with a stronger appetite for digital agriculture are the EU, USAID, and the African Development Bank.
7	Kulykovets (2023)	Automation of Production Processes in Agriculture Using Selected Artificial Intelligence Tools	Through AI4D, Villgro funded
8	Qiao (2022)	Editorial: AI, Sensors and Robotics in Plant Phenotyping and Precision Agriculture	No Funding Received

9	Qiao (2022)	Editorial: AI, Sensors and Robotics in Plant Phenotyping and Precision Agriculture	No Funding Received
10	Rozenstein (2024)	Data-Driven Agriculture and Sustainable Farming: Friends or Foes?	No Funding Received
11	CGIR 2023	Three Ways That Machine Learning Can Bring Precision Agriculture to Small-Scale Farms	No Funding Received
12	Zhang (2024)	Editorial: Artificial Intelligence and Internet of Things for Smart Agriculture. | EBSCOhost	No Funding Received
13	Zhang (2024)	Achieving the Rewards of Smart Agriculture. | EBSCOhost	Yes (does not specify)
23	Sheikh (2021)	IoT and AI in Precision Agriculture: Designing Smart System to Support Illiterate Farmers	No Funding Received

Table 7: Findings from the thematic analysis

Main Theme	Sub-Theme	References
Equity	Demographic of farmers and users	Couette (2024); FAO (2024); Hossain (2022); Owino (2022); Sheik (2021); Sparrow et al (2022); Thortsen et al (2022); UNDP (2024); Yasabu (2019)
	Digital divide	Owino (2022)
Inclusion and accessibility	Accessibility	Couette (2024); FAO (2024); Hossain (2022); J-Pal (2022); Thortsen et al (2022); Owino (2022)
	Digital literacy	Owino (2022); FAO (2024); Hossain (2022); J-Pal (2022)
Role of organisations	Funders	Dixit & Gill (2024); FAO (2024); IDRC (2023); IDRC (2023); Owino (2022); Thortsen et al (2022); UNDP (2024); Yasabu (2019); Zhang et al (2024); Zhang et al (2023)
	Users	Couette (2024); Dixit & Gill (2024); IDRC (2023); IDRC (2023); Thortsen et al (2022); UNDP (2024); Yasabu (2019)

	Beneficiaries	FAO (2024); IDRC (2023); IDRC (2023); Thortsen et al (2022); UNDP (2024); Yasabu (2019)
	Implementors	Couette (2024); FAO (2024); Gupta et al (2023); IDRC (2023); Thortsen et al (2022); UNDP (2024); Yasabu (2019); J-Pal (2022)
	Developers	Couette (2024); IDRC (2023); UNDP (2024); Yasabu (2019)
Ethics and governance	Ethics	Owino (2022); FAO (2024); Hossain (2022); Kulykovets (2023); Sparrow et al (2022); Thortsen et al (2022)
	Governance	Owino (2022); FAO (2024); Hossain (2022); Kulykovets (2023); Offer et al (2024); Sparrow et al (2022); Thortsen et al (2022)

Details for stakeholder engagement

The following themes and questions were identified for the first workshop:

Theme I: AI-enabled solutions in agriculture
Question for the panel: What are some of the prevalent AI-enabled solutions employed in different agricultural target problems?
The session aimed to explore various AI-led solutions used in different target problems in agriculture. The discussion also sought to shed light on the need for contextually relevant AI-led solutions, especially in L&MICs, and for smallholder farmers.

Theme II: Inclusive design and user diversity
Question for the panel: What role does diversity play in influencing the AI uptake for beneficiaries and the AI scale-up for developers?
The session focused on understanding the different dimensions of diversity (such as farm size, gender, age, and digital literacy) that influence the uptake of AI in agriculture. Additionally, the research team engaged stakeholders to identify key barriers and opportunities for creating inclusive, user-centred AI-enabled solutions**.**

Theme III: Sustainability of AI-led solutions in agriculture
Question for the panel: What are sustainable AI-enabled solutions? What are some of the collaborations required to ensure sustainable AI-enabled solutions in agriculture?
This session emphasised the importance of sustainability in the use of AI in agriculture. It covered aspects such as environmental considerations, robust governance structures, and social welfare implications. Discussions also focused on best practices and collaborative approaches towards developing and maintaining sustainable AI-led agricultural solutions. Additionally, our team also anchored discussions on practices to help create sustainable AI-led solutions.

Table 8: List of participants in stakeholder engagement 01

S. no	Stakeholder Engagement Participants
1	Beryl Winnie Atieno Agengo
2	Dona Mathew
3	Berber Kramer
4	Tippins Stuart
5	Wayan Vota

For the Second workshop, the following themes and guiding questions were identified:

Theme I: Need for regulatory framework

Question for the panel: Are there regulatory infrastructures or frameworks in place to ensure ethics and equity compliance? What are some of the risks associated with ethics or equity compliance and are there mitigation strategies in place?

The session examined how regulatory structures facilitated the scaling up of AI-enabled solutions in agriculture. Stakeholders were invited to reflect on the existence and adequacy of regulatory mechanisms that ensure compliance with ethics and equity considerations. The discussion also explored potential risks associated with these frameworks, and identified mitigation strategies.

Theme II: Investment, innovation, and AI uptake

Question for the panel: What investments and innovations, in your opinion, can be implemented to incentivise AI uptake for smallholder farmers?

Researchers used this session to encourage stakeholders to discuss how a supportive environment can foster investment and innovation for small-scale farmers in L&MICs. Such an environment can also boost the uptake of these solutions.

Theme III: Horizon mapping

Question for the panel: What are some of the factors that can help drive momentum for AI-enabled solutions and ensure sustained usage (e.g., digital inclusion and literacy, extension services, and digital awareness)?

The concluding session explored potential short-, medium- and long-term trajectories of AI in agriculture.

Table 9: List of participants in stakeholder engagement 02

S. no	Stakeholder Engagement Participants
1	Aniruddha Brahmachari
2	Carolina Salmeron
3	Castillo Leska
4	Ana

5	Jona Repishti
6	Najeeb Abdulhamid
7	Narendra Kandimalla
8	Nitish Kumar
9	Nupur Mishra
10	Prerak Shah
11	Rikin Gandhi

Details for case study and deep dives

African case study interview guide

Research questions: Tulime Tuvune case study on AI in agriculture in the SSA context

Introduction - Please explain your solution in detail, what it offers, what tech it is using, at what stage it is, and what are your future plans for improvement.

1. Perceived benefits and challenges: How do you anticipate the benefits and challenges of integrating your AI application into the targeted agricultural value chains?
Probe: Who are your main target groups, and how do their specific needs shape the solution you are offering? What is your mission and vision, and how do you aim to achieve this?

2. Adoption and implementation: What factors influenced the decision of your target groups to adopt AI technologies in their agricultural operations?
Probe: Are there particular groups that are not adopting your solution? If so, why do you think this is happening? What are the motivations and barriers for adopters and non-adopters, respectively? What strategies are in place to address this?

3. Impact on productivity: How has the use of your AI tool affected crop yields, resource efficiency, operational productivity, food security, and farmer livelihoods among target groups? **Probe:** Can you share specific success stories or examples of how your solution has made a difference?

4. Usability and accessibility: How user-friendly and accessible is your AI solution for different agricultural groups in the SSA context?
Probe: What process did you go through to make your solution user-friendly and accessible? Are there groups facing critical access issues (e.g., issues related to connectivity, language, or digital literacy)? What are these issues, and how are you addressing them?

5. Economic considerations: What are the projected economic implications (e.g., costs, savings, return on investment) for farmers using your AI solution?
Probe: Are these economic benefits already evident among farmers using your solution? If not, what other indicators are you using to measure the economic impact?

6. Sustainability and environmental impact: In what ways does your AI solution contribute to sustainable farming practices and environmental conservation in SSA?
Probe: Are there any unintended environmental challenges or risks associated with your solution? How are you mitigating them? What are your strategies to potentially mitigate environmental risks?

7. Future potential and recommendations: What future improvements or features would you like to integrate into your AI application to address gaps in accessibility, usability, economic outcomes, and sustainability?
Probe: Are there partnerships, technologies, or strategies you're exploring to help bridge these gaps? What kind of business and revenue model do you intend to adopt for economic sustainability?

Table 10: List of Participants in the African Case study

S. no	Name	Role/Title
1	David Muriba	Tulime Tuvune co-founder and developer
2	Brian Gacheru	Tulime Tuvune co-founder and developer

3	Patrick Wekesa (Pseudonym)	Kictanet AI in Community Researcher
4	Ruth Nyambura (Pseudonym)	Farmer
5	James Mugedi (Pseudonym)	Farmer
6	Grace Chemutai (Pseudonym)	Policy Maker

Asian Case study interview guide – Saagu Baagu

Purpose of the study: The landscape analysis was conducted to study the effectiveness of AI-enabled solutions in agriculture in L&MICs. This landscape analysis consisted of multiple methodologies such as a rapid review, narrative synthesis, stakeholder engagements, typology analysis, deep dives, and case studies.

Purpose of the interview*:* This interview was conducted to address some key information gaps found during the desk research of the Saagu Baagu case study. The research team aims to contact stakeholders named in Saagu Baagu's policy documents. This will provide a clearer picture of the on-the-ground realities of an ongoing PPP in L&MICs such as India. **Background of the case***:* Saagu baagu is a PPP that aims to re-shape Telangana's agricultural landscape by leveraging emerging technologies like artificial intelligence in an "inclusive, scalable, and sustainable" manner. Smallholder farmers are the primary target. The main reason for conducting a case study is to understand the impacts of large-scale artificial intelligence projects on L&MICs.

Overview of gaps:

Stage 1: Pilot - 18-month pilot

- They claim an 'inclusive' deployment, but lack specific definitions. Who is included, and who is being excluded. How are the exclusions being addressed?
- They acknowledge technology diffusion challenges due to poor reception by smallholders. Beyond this statement, how are they actively addressing this resistance?

- Beyond current issues, what are the literacy and AI adaptation hurdles?
- Do they see any opportunity costs in deploying AI in L&MICs?
- Are these PPPs the main plan for deploying AI in agriculture? Or are they open to other kinds of investments?
- What is the government's general policy on data protection, and how does it balance data security with the rights of farmers, particularly regarding their data?

Stage 2: Current stage

- Improvements made from the main learnings of the pilot stage.
- How are they planning to scale it and diffuse it into the market to ensure financial sustainability?

Interview questions for the university involved in Saagu Baagu.

Dr Praveen Rao Velchala (31/01/2025)

Dr Praveen Rao Velchala is the current Vice Chancellor of Kaveri University and the Former Vice Chancellor of Prof Jayashankar Telangana State Agriculture University. He was involved in the Saagu Baagu initiative through his former university and has contributed to the report produced by the WEF. He is an expert in the field of agriculture.

- Introduction Round
- Consent to take a transcription
- Explanation of the interview
- Firstly, we would like to begin by acknowledging the valuable work that you are doing in this area; especially at the scale at which it has been done. It is also very interesting and important that you are focusing on the transition into digital and artificial intelligence solutions in agriculture, with smallholders in mind. We had a couple of questions as we had some access issues when we were doing our desk

research. We think it is important to reach out to the various stakeholders who were a part of Saagu Baagu's inception to fill in some of these gaps, and gain deeper insights into the project.

Pilot stage:

- We wanted to start off by asking why was Telangana the ideal spot for taking up this project?
- What are some suggested best practices from the pilot stage?
- We found that the main challenge was to change traditional ways of thinking. What are your views on how the project has been adapted by smallholder farmers?
- We had some trouble accessing information on the role of women smallholder farmers in agriculture. Do you have any insights on this or could you connect us to anybody who worked closely with women farmers in the area?
- What do you think is the role of universities and other knowledge institutes in PPPs?

General questions and future outlook:

- What do you see for the future of this project in terms of scale?

Lastly, we would greatly appreciate it if you could guide us towards other contacts and stakeholders associated with the project. We would also appreciate any relevant documents or information sources on this.

Interview questions: Funders

Dr. Srivalli Krishnan – BMF (12/02/2025)

Dr. Srivalli Krishnan is a Senior Programme Officer for Asian Agriculture Development at the Bill & Melinda Gates Foundation. She was the key programme officer involved from The Gates Foundation in Saagu Baagu. She is an expert in agricultural development issues and has previously worked as a Development Assistance Specialist in the Indian branch of the USAID.

- Introduction round
- Consent to take a transcription
- Explanation of the interview
- Firstly, we would like to begin by acknowledging the valuable work that you are doing in this area; especially at the scale at which it has been done. It is also very interesting and important to us that you are focusing on the transition into digital and artificial intelligence solutions in agriculture, with smallholders in mind. We had a couple of questions as we had some access issues when we were doing our desk research. We thought it would be important to reach out to the people who were a part of Saagu Baagu's inception to fill in some of these gaps and gain deeper insights into the project.

Pre-pilot:

In an interview with ICRISAT, you mentioned that the key to forming a public-private partnership is to have a shared goal. How did the various stakeholders form the shared goal in the context of Saagu Baagu?

- As a funding organisation, how would you approach identifying regions during the pre-pilot phase in the creation of a PPP?

Pilot:

- What are some suggested best practices from the pilot stage?
- What is your view on the uptake of the project in the Telangana region?
- If you were to go back to designing this project with the learnings of the pilot stage, what are some changes you would make in your plan?
- According to you, what are the main successes of the pilot phase of this project?
- According to you, what were the challenges faced during the pilot stage?

Role of women:

- We had some trouble accessing more information regarding the role of women smallholder farmers in agriculture. We were wondering if you have any insights on this.
- We would also love to hear your thoughts on digital inclusion and digital accessibility.

Scalability:

- You also noted in the video I mentioned earlier that shared goals help in scalability. According to you, has this manifested in the case of Saagu Baagu?

Governance:

- In our desk search, we found it challenging to find information about governance mechanisms that are put in place for public-private partnerships. Could provide us with more information on this?

Lastly, we would be grateful if you could guide us towards other contacts and stakeholders associated with the project, as well as share any relevant documents or information sources.
Interview Questions: Implementing partners (05/02/2025)

Theme 1: Primary goals

- According to you, what are the core goals and priorities of the AI4AI initiative, and how do these align with broader agricultural development objectives?

Theme 2: Discussion of smallholder farmers

- Why do you think smallholder farmers are a central target for AI4AI, and what unique challenges and opportunities do they present in the context of AI adoption? What specific problems are they facing that AI can help solve?

Theme 3: Regional relevance and strategic selection

- What factors made Telangana an interesting region for the WEF's agricultural initiatives?

Theme 4: Targeting agriculture for AI

- What are the essential steps and considerations involved in designing and implementing a successful pilot stage for an agricultural AI project?

- What do you think are some key performance indicators (KPIs) for the implementation of projects like Saagu Baagu?
- What are some common pitfalls to avoid during the pilot stage, and how can these challenges be mitigated?

Theme 5: Best practices and challenges

- What were some of the most significant hurdles encountered during the implementation of AI in agriculture projects, particularly in smallholder farming contexts?
- Would you say that these challenges can be addressed through effective strategies, partnerships, and community engagement?

Theme 6: Inclusion

- What do you think is the current role of women and other marginalised groups in the development and application of AI in agriculture? What is the gender gap?
- What is the role of an organisation like the WEF in empowering women to use AI tools in agriculture?

Theme 7: Looking through the various AI4AI initiative

- Do you see any similarities and differences between various AI4AI initiatives around the world?
- What, in your opinion, are best practices shared and adapted across different AI4AI projects to maximise their impact?

Theme 8: Scaling

- What do you think are the key strategies state governments have implemented to effectively scale up the use of AI in agriculture, especially for smallholder farmers?
- How do you think governments can create an enabling environment for AI adoption, including infrastructure development, data sharing, and capacity building?
- What role can public-private partnerships play in scaling AI-enabled solutions and ensuring their sustainability?

Theme 9: Key governance dimensions

- What key governance dimensions did the WEF need to consider when implementing its AI in agriculture projects?
- What is your view on WEF's approach towards data privacy, security, and ethical use of AI technologies in its initiatives?
- How would you say WEF engaged with local communities and stakeholders to ensure that its projects were aligned with their needs and priorities?

Interview questions: government - planned – 03/02/2025 (Cancelled)

Jayesh Ranjan

Mr Jayesh Ranjan, IAS is the Special Chief Secretary, Information Technology (IT) & Industries and Commerce (I&C), Government of Telangana.

Pilot stage:

- Macro level – what was the reason?
- We wanted to ask why Telangana was the ideal spot for taking up this project.
- What are some suggested best practices learned from the pilot stage?
- We found that the main challenge was to change traditional ways of thinking. What are your views on how the project has been taken up by smallholder farmers?
- We had some trouble accessing more information regarding the role of female smallholder farmers in agriculture. Do you have any insights on this? Could connect us to anybody who has worked closely with female farmers in the area?
- What do you think has been the biggest lesson from the pilot stage?
- What do you think is the role of government in PPPs?

General

- The WEF report mentioned PPPs as a key strategy for deploying AI in agriculture. Could you tell us about your approach to investment and collaboration with various stakeholders?
- We would also like to ask you a general question regarding your view on hard regulation for AI in India and how that could affect agriculture. (Note: There is a lot of discourse within the government about whether AI regulations should be implemented or not. It would be interesting to know what the interviewee thinks about governance mechanisms.).

Interview questions: Pilot implementation partners (17/02/2025)

Nidhi Bhasin & Narendra Kandimalla from Digital Green

Nidhi Bhasin

CEO of Digital Green for India

Narendra Kandimalla

Head of AP and TS Region

Pilot stage:

- In your opinion, what are the best practices for implementation partners during the pilot stage of Saagu Baagu?
- How were the CRPs appointed, and according to you, how have they helped the process of Saagu Baagu?
- During our desk research we found a lot of yield metrics, which contributed to the success of this project. How this data is collected?
- What were some challenges that you faced as implementation partners during the pilot phase, and what were the solutions?
- What role does data governance play for Digital Green when involved in a multi-stakeholder project?

Latin American case study - interview and case study guide: AI-enabled solutions in Brazilian agriculture

This guide is designed to facilitate a structured interview and case study analysis of SciCrop, an AI-driven agtech company in Brazil. The objective is to explore the company's technological innovations, impact, and challenges in the agricultural sector.

Interview guide

Holding three interviews with the CEO ensured a comprehensive understanding of SciCrop's AI-enabled solutions in Brazilian agriculture. The reasoning behind this approach is:

1. **Depth and detail** – Multiple sessions allowed for follow-ups and deeper insights to capture the full scope of the company's vision, strategy, and challenges.

2. **Progressive inquiry** – The first interview explored the company's background and strategy, the second addressed technical and operational aspects, and the third validated findings and discussed next steps.

3. **Contextual adaptation** – AI applications in agriculture involve multiple stakeholders (farmers, policymakers, technologists). Speaking with the CEO at different stages ensured alignment with evolving perspectives and external developments.

4. **Cross-verification** – Insights from other sources and peer-reviewed materials were revisited with the CEO for confirmation and refinement, ensuring accuracy in the case study.

Initial interview

General background

1. Can you provide an overview of SciCrop's mission and vision?

2. How did SciCrop start, and what inspired its creation?

3. What are the key milestones in SciCrop's development?

AI-enabled agricultural solutions

1. What are the main AI-driven solutions that SciCrop offers?

2. How do these technologies work, and what data sources do they rely on?

3. Can you provide specific examples of how SciCrop's AI-enabled solutions have improved agricultural productivity or efficiency?

Implementation and adoption

1. What are the main challenges farmers and agribusinesses face in adopting AI-enabled solutions?

2. How does SciCrop support clients in integrating AI into their operations?

3. What is the level of AI adoption in Brazilian agriculture, and how does SciCrop contribute to its growth?

Ethical and regulatory considerations

1. What ethical considerations does SciCrop take into account when deploying AI-enabled solutions?

2. How does SciCrop handle issues related to data privacy and security?

3. Are there any regulatory challenges that impact the implementation of AI in Brazilian agriculture?

Future prospects and innovations

1. How does SciCrop plan to expand or innovate its AI-enabled solutions in the coming years?

2. What trends do you foresee in AI applications for agriculture in Brazil and Latin America?

3. How can government policies and industry collaborations support the growth of AI in agriculture?

Second interview

1. How is SciCrop currently integrating AI technologies into its agricultural solutions, and what specific challenges are you addressing within the industry?

2. Can you describe a real-world example where AI has significantly improved crop management or yield prediction on farms using your platform? What measurable outcomes have you seen?

3. What role do local data collection and machine learning play in SciCrop's decision-making process, and how do you ensure the quality and accuracy of the data being used by AI models?

4. You mentioned pilot programmess have already been conducted in several countries, including USA, the Netherlands, and Portugal. Can you share if there are any other countries and what these tests entail?

5. In your opinion, what are the biggest barriers farmers face when adopting AI-driven tools, and how is SciCrop working to overcome these obstacles?

6. Looking ahead, how do you envision agricultural AI evolving over the next 5-10 years, and what innovations or trends are you most excited about in terms of future impact on farming?

7. Can you walk us through the process of developing an AI model for a specific agricultural task, such as crop disease detection or yield prediction? What are the key steps from data collection to deployment?

8. How do you ensure that the AI algorithms you develop are adaptable to the diverse environments and varying data quality encountered across different farms? What challenges do you face in making these models robust and scalable?

9. AI models often require continuous monitoring and refinement. How do you handle ongoing updates and improvements to the AI models once they are deployed in the field, and how do you incorporate feedback from farmers into the development cycle?

Ethical concerns of using AI in agriculture

10. AI in agriculture has the potential to revolutionise farming, but it also raises concerns about data privacy and security. How does SciCrop address these ethical issues, particularly regarding the collection and use of sensitive farm data?

11. As AI-driven tools are integrated into agriculture, there's a risk of widening inequalities between large-scale farms and smaller, resource-limited ones. How does SciCrop ensure that its AI-enabled solutions are accessible and beneficial to all farmers, regardless of their size or technological capabilities?

12. Do you have any data on the use of the platform by female farmers? Any insights different from men?

Final interview

1. Where does SciCrop operate, and what platform is being used for the solution (Is it web-only? an app?) Can you dig deeper into the products and the algorithms? Also, how have you localised or contextualised the solution? Which crops and ecosystems are they targeting?

2. You mentioned you have collaborated with other countries. Does this mean that you worked together on developing the AI solution, or did these companies use or buy the SciCrop solution? Can we include information on which companies these were? The same applies to those in São Paulo and other Brazilian cities. If company names are not available, we could add the agricultural crops or products they work on.

3. The website states that: ’The SciCrop development team is a cross-disciplinary group including data scientists, agronomists, engineers, and software developers who work closely with agricultural experts to ensure the AI models align with real-world farming practices.’ Can you provide more information on what 'to ensure the AI models align with real-world farming practices' means, or what this cross-disciplinary group does?

4. We also talked about ’local or state government bodies focused on agriculture and climate adaptation policies, which have benefited from insights provided by SciCrop’s AI models, informing better agricultural policies.’ Can you explain further which governments? How have they benefited? Which data was shared?

5. Talking about the pilots you ran in France and Netherlands; can you tell me what types of data you got from these pilots in the EU and how that helped the Brazil platform and products? How is this data relevant to small and medium enterprises or farms?

6. In an interview with BM&C News in 2024, you said ’The platform has made strides to localise content and interface, but there is ongoing work to make it more accessible.’ Can you please talk to me about how you are making this happen?

7. We talked about the challenges some people have in using SciCrop. Can you tell me more about why farmers don't have timely access to the data? Are farmers expected to enter data, thereby causing a time-lag between when data are collected, and when farmers submit this data to SciCrop?

8. You also talked about how ’farmers need adequate training to fully utilise the platform’ and how ’the team has collaborated with local agricultural extension services to provide training, but scaling this remains a concern.’ Can you tell me what the farmers need training on, and why scaling is a concern?

9. In the previous interview, you mentioned that ’the team also works closely with local agricultural experts and community leaders.’ Can you tell me more about what capacity and what kind of information you get from them?

10. We also discussed how ’the team is continuously gathering feedback from its clients.’ Can you explain if it's through the infinity stack? How do you collect feedback through this? And what is the feedback you are asking for? What is in the data catalogue? What does this observability software observe, and what data do they engineer?

Case study framework

A. Introduction

    a. Brief overview of the case study’s objectives.

    b. Background on SciCrop and its role in AI-driven agriculture in Brazil.

B. Context and industry landscape

    a. Overview of Brazilian agriculture and key challenges.

    b. Role of AI in addressing these challenges.

C. SciCrop’s AI-enabled solutions

    a. Description of SciCrop’s technology and services.

    b. Case examples demonstrating the impact of AI-enabled solutions.

D. Analysis of adoption and challenges

    a. Factors influencing AI adoption in Brazilian agriculture.

    b. Barriers and opportunities for AI-driven solutions.

E. Ethical and regulatory considerations

    a. Key ethical issues related to AI in agriculture.

b. Overview of relevant regulations and compliance measures.

F. Future outlook and recommendations

a. Potential advancements in AI for agriculture.

b. Policy and industry recommendations for scaling AI adoption.

G. Conclusion

a. Summary of key insights and takeaways.

b. Final thoughts on the role of SciCrop in advancing AI for agriculture.

Data collection and analysis methods

1. Primary Data: Interviews with SciCrop executives and stakeholders.
2. Secondary Data: Analysis of industry reports, academic studies, and market data.
3. Comparative Analysis: Evaluation of SciCrop against similar AI-driven agricultural initiatives.

Table 11: List of participants in the Latin American case study

S. no	Name	Role/Title
1	José Damico	CEO and Co-founder of SciCrop
2	Kieran Gartlan	Managing Director of The Yield Lab Latam

Table 12: Types of analysis that the SciCrop platform offers to its clients.

Type of analysis	What does it mean?	Example in agriculture
Descriptive	Summarises and measures past data to provide an accurate picture of what has happened. It focuses on identifying trends, patterns, and key metrics.	Measuring the extent of low productivity in a season's crop based on past yield data.
Diagnostic	Identifies causes and relationships between factors using historical data. It seeks to answer why something happened.	Analysing weather patterns and soil quality to determine why crop productivity was lower than expected.
Predictive	Uses statistical models and machine learning techniques to forecast future outcomes based on historical data. It assesses risks and probabilities.	Predicting a potential decrease in crop productivity due to an upcoming drought based on past weather patterns and soil moisture data.
Prescriptive	Recommends actionable strategies based on predictive insights. It suggests steps for optimising outcomes.	Advising farmers to increase irrigation frequency from twice a day to four times a day in response to an anticipated drought.

Table 13: SciCrop's product costs.

Product	Cost and Description

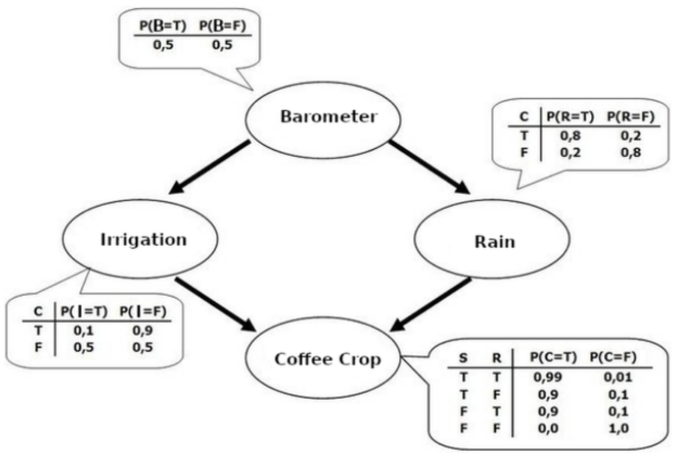
FARMGIS	Starter plan - free For small producers or for anyone to test. Up to 50 hectares Up to 1 plot Up to 5 users	GIS plan - R$790/mês (around $136 USD) For large producers and geoprocessing departments. Up to 50,000 hectares Up to 50 plots Up to 50 users	Unlimited plan - R$790/mês (around $256 USD) For corporations, extensionists, and integrators with multiple clients. Unlimited hectares Unlimited plots Unlimited users Personalised support
PLUVIO	Starter plan – free For those who just need to know what the weather conditions were like. 1 collection point Current weather in the city	Virtual plan - R$29.90point/month (around $5 USD) For those who need greater assertiveness and climate forecasting. Multiple collection points Current weather in the city	Station plan - R$299.90point/month (around $52 USD) For those who need a localised forecast with a weather station. Multiple collection points Current weather in the city Historical data of the municipality

	Historical data of the municipality	Historical data of the municipality 15-day forecast for the municipality Satellite hyperlocal precipitation	15-day forecast for the municipality Satellite hyperlocal precipitation Leased meteorological station Current weather at the station Historical station data 15-day forecast by station Weather alerts by season
InfinityStack	Farmer plan - $2000 USD/month For farmers and SMEs looking to start the data integration journey. All features included Up to 3 integration projects 1 TB cloud included Dashboards in Grafana		Corporate plan -$6000 USD/month For corporations with multiple systems integrations and seeking to add AI to operations. All features included Unlimited integration projects Set up in the customer’s cloud Dashboards in Grafana Personal support

	Optional - dedicated team (additional cost)	Optional - dedicated team (additional cost)
WEBFARMS	Varies according to the request of the client.	

Figure 19. Working of Bayes' probabilistic model work by SciCrop.

How does a bayes probabilistic model work?



What Each Letter Represents in the Diagram:

B (Barometer) – Barometer Reading
B = T: The barometer indicates rainy weather (True).
B = F: The barometer indicates good weather (False).

R (Rain) – Rain
R = T: It is raining (True).
R = F: It is not raining (False).

I (Irrigation) – Irrigation
I = T: Irrigation has been applied (True).
I = F: No irrigation was applied (False).

C (Coffee Crop) – Coffee Crop Condition
C = T: The crop has adequate water supply (True).
C = F: The crop lacks adequate water supply (False).

How to read it:
P(R=T | B=T) = 0.8
This means that if the barometer indicates rainy weather (B=T), the probability of it actually raining (R=T) is 80%.

P(I=T | B=F) = 0.5
This means that if the barometer indicates good weather (B=F), there is a 50% chance that irrigation will be applied (I=T).

P(C=T | I=T, R=F) = 0.9
This means that if irrigation was applied (I=T) and it did not rain (R=F), the probability that the coffee crop is in good condition (C=T) is still 90%.

Explanation:
The Barometer (B) is the initial point of analysis since it influences both Irrigation (I) and Rain (R). Then, the impact of these two variables (I and R) combines to determine the condition of the Coffee Crop (C).

The Bayesian model allows us to update these probabilities as new information becomes available.
For example:
If you observe that the barometer indicates rain (B=T), you can calculate the probability of actual rain (R=T) and the likelihood of irrigation (I=T).
With this information, you can estimate the final probability that the coffee crop is in good condition (C=T).

Global case study

Table 14: List of participants in global case study

S. no	Name	Role/Title
1	Jona Rephisti	Assistant Director, Global Gender, Digital Green

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