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Digital Planet
Where Digital Innovation Meets the World
IDEA 2030

Getting Real About AI for the Bottom-of-the-Pyramid:

Improving the Economic Outcomes of Smallholder Farmers in Africa

A roadmap for harnessing the potential of AI-enabled crop protection technology to enhance yields and deliver dividends at scale to rural communities across the continent.

IDEA 2030 is Supported by the Mastercard Center for Inclusive Growth

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About

Who We Are

Digital Planet

Digital Planet, an interdisciplinary research initiative of The Fletcher School's Institute for Business in the Global Context, is dedicated to understanding the impact of digital innovations on the world and providing actionable insights for policymakers, businesses, investors, and innovators.

Imagining a Digital Economy for All in 2030 (IDEA 2030)

IDEA 2030 is a Digital Planet research initiative aimed at fostering inclusive growth around the world using the power of digital technologies.

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The Institute for Business in the Global Context (IBGC) connects the world of business to the world. It is the hub for international business at The Fletcher School, the oldest graduate school of international affairs in the United States. The Institute takes an interdisciplinary approach, preparing global leaders who can cross borders of many kinds and integrate business skills with an understanding of the geopolitical, legal, financial, security, macro-economic, humanitarian, and environmental impacts on business. The Institute is organized around four core activity areas: education, research, dialogue, and a lab. Our degree programs – Master of International Business (MIB) and Master of Global Business Administration (GBA) – and leadership development programs are at the heart of our educational mission. These offerings, coupled with original research in multiple areas – inclusive growth, digitalization, innovation and economic development at scale, sovereign wealth, and global capital flows, among others – facilitate a vibrant dialogue on contemporary global issues through conferences, symposia, and speaker events. The lab creates opportunities for student teams to take knowledge into the field, affecting change through entrepreneurial start-ups and consulting projects. The Institute also houses the Council on Emerging Market Enterprises, a think tank comprising distinguished practitioner-scholar experts who collaborate with the Institute and The Fletcher School on a variety of initiatives, such as research programs, symposia, and conferences.

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center for inclusive growth

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Executive Summary

Agriculture, a linchpin of Sub-Saharan Africa's economy, confronts formidable challenges, including stagnating productivity and low yields exacerbated by climate change. Agriculture employs an estimated 65-70 percent of Africa's labor force and accounts for approximately 30-40 percent of its GDP.[1] Yet, the continent remains a net importer of food, leading to food price inflationary pressure.[2] With yields in Africa trailing other regions like Asia and the Americas, and 60 percent of the available arable land in the world,[3] there is ample opportunity for significant improvements. Tools and technologies like better seed varieties, greenhouses, and fertilizers hold promise. This study delves into one of these tools, Artificial Intelligence (AI), which has the potential to help smallholder farmers improve productivity at a low cost. We examine the economic implications of this AI tool for smallholder farmers and rural communities in Sub-Saharan Africa.

In SSA, over 80% of farms are managed by resource-constrained smallholder farmers (SHFs) who cultivate in challenging circumstances with lower levels of productivity than farmers in the rest of the world.[4] Boosting crop yield normally requires significant additional investments – a financial hurdle far too high for the average smallholder farmer, who typically has a lower income and limited access to capital and commodity markets. Farmers are in critical need of tools to mitigate crop losses while minimizing financial burdens. Given that SSA farmers lose an estimated half of their crops to pests each year, a low-cost tool to reduce crop loss could improve the productivity of farms and boost the incomes of farmers.[5]

There are several ways in which the use of data analytics and AI in farming practices can improve crop yields in African farms. Our report takes a specific application: Crop Protection AI (Crop AI), which improves yields through disease detection and pest protection, and is a readily adoptable solution tailored to SSA's agricultural landscape. Due to its scalability, low entry cost, and alignment with the digital literacy levels of rural farmers, Crop AI stands out as a promising solution. Crop AI technology offers pest and disease diagnosis, deficiency analytics, and precise guidance on pesticide application. This precision prevents indiscriminate pesticide use, reduces pesticide pollution,[6] and fosters cost savings for farmers.

Crop AI technology can address the unique challenges faced by SSA's SHFs. Beyond tackling crop loss, large-scale adoption of Crop AI empowers farmers with digital tools that enhance productivity, promote sustainability, and contribute to the region's economic development.

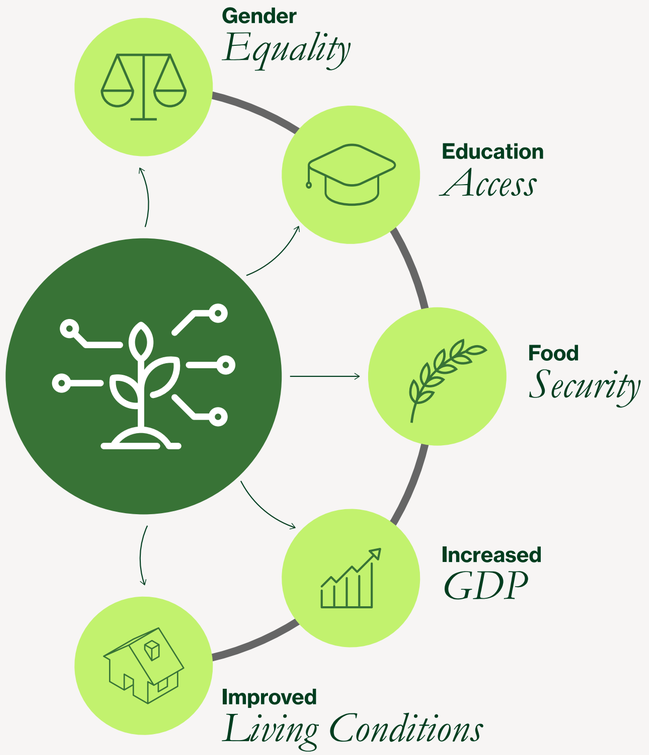
There are several ways in which AI interventions can affect farmer productivity. The advantage of this AI-enabled solution is its accessibility through any smartphone with internet connectivity and ease of use,

requiring minimal digital literacy. For example, using the Plantix app, the one we used for our model, a farmer can take a picture of a sick crop, upload it to the app, and receive a diagnosis and treatment, along with prevention methods for future crops. This information can be delivered via audio in a locally appropriate language, eliminating the requirement for literacy. If deployed, this low-cost, scalable AI solution can make an immediate, measurable impact on SHF productivity, directly addressing the critical issue of crop loss.

Given that SHFs are often the most economically marginalized, any technology enhancing their revenue directly uplifts these communities. With over a third of the global food supply produced by smallholder farmers,[7] Crop AI technology has the potential to create ripple effects on the entire value chain, enhancing food security and aligning with key UN Sustainable Development Goals.

The following evaluation framework assesses the impact of this cost-effective, smartphone-accessible Crop AI tool on crop yield and revenue at both micro and macro levels. This assessment evaluates the technology's potential to uplift the most vulnerable communities, improve food security, and contribute to sustainable development goals, including SDG 1 – reducing poverty, SDG 2 – reducing hunger and promoting sustainable agriculture, SDG 4 – quality education, SDG 5 – gender equality, SDG 8 – promoting sustained economic growth, and SDG 10 – reducing inequality.

The following report outlines the path to unlocking an additional USD 6.1 billion in revenue across seven SSA countries. Of this improvement, USD 1.5 billion is anticipated to directly impact 14.3 million smallholder farmers growing each country's top five crops and potentially provide 8.9 million children with access to education annually.



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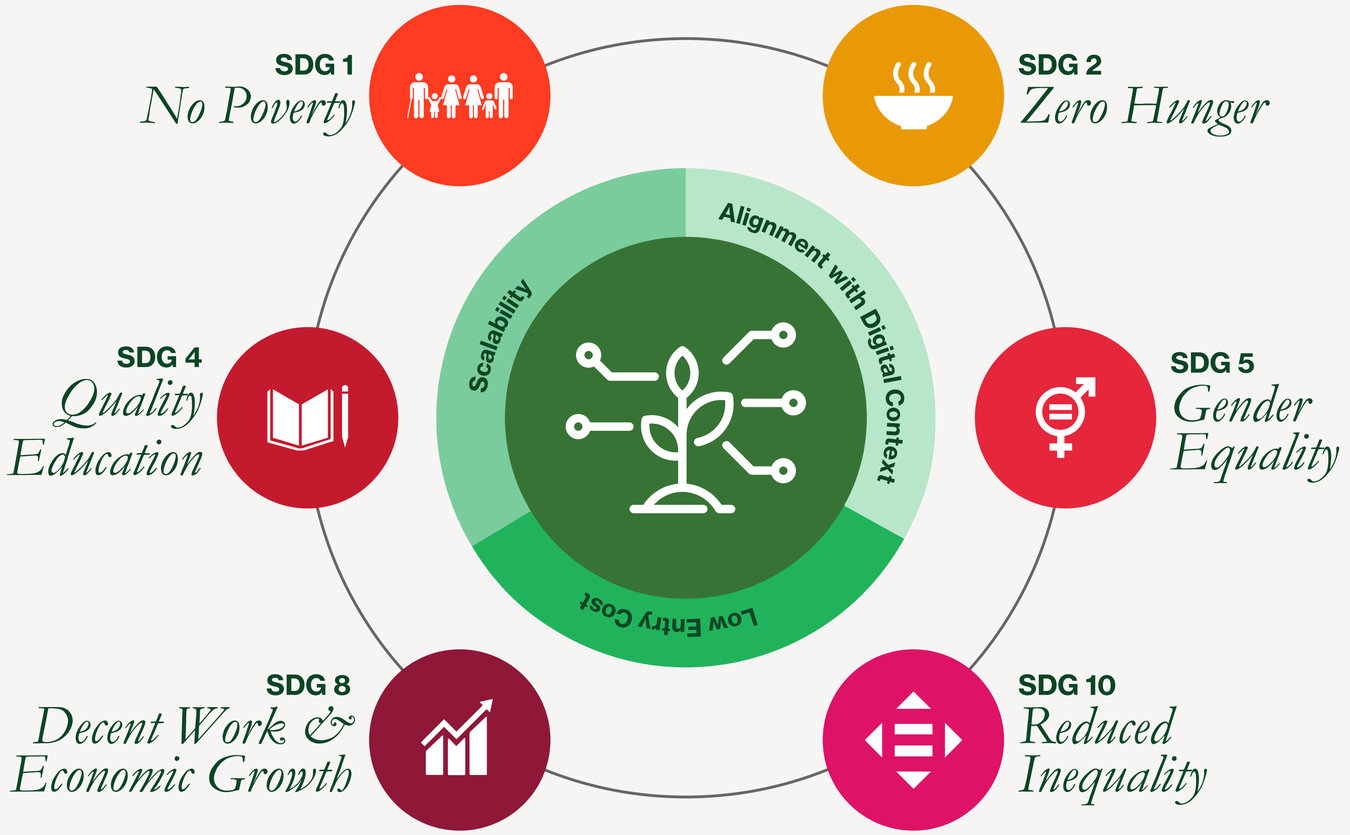

32%

of the global food supply is produced by SHFs[8]

80%

of SSA farms are managed by resource-constrained SHFs[9]

Emerging Insights

A considerable economic opportunity is on the horizon for Sub-Saharan Africa's (SSA) agricultural sector, forecasting an estimated USD 2.7 billion revenue upswing through the adoption of a streamlined Crop AI technology. The realization of this transformative impact is contingent upon the active participation of seven agriculture-dominant economies: Côte d'Ivoire, Ethiopia, Kenya, Nigeria, Rwanda, Tanzania, and Uganda. Importantly, this growth can be achieved without necessitating additional technological adjustments.

The implementation of the policies recommended in this study promises a substantial revenue gain in addition to the already expected USD 2.7 billion; policy implementation can increase economy-wide dividends by USD 3.4 billion, culminating in a USD 6.1 billion surge in revenue for the agricultural sector and the economy as a whole.

This economic boost is poised to directly benefit between 6.4 million and 14.2 million smallholder farmers (SHFs), a demographic typically positioned at the lower echelons of the economic spectrum. The supplemental USD 653 million to USD 1.5 billion in direct revenue to farmers holds the potential to markedly improve living conditions for SHFs, leading to better outcomes in areas such as nutrition and education.

An expected average rise in individual farmer revenue by USD 102 per planting cycle emphasizes the concrete and prompt influence on the economic well-being of this vulnerable demographic. While this additional revenue may appear modest, its impact on farmers' living expenses is significant. For instance, in the examined countries, despite government subsidies for elementary and secondary education, households still bear additional financial responsibilities such as the cost of books and uniforms. Notably, one in five children ages 6 to 11 are out of school, and only two-thirds of children between ages 12 to 14 are in school in Sub-Saharan Africa.[10] The increased revenue from adopting this technology can readily contribute to educating at least 8.9 million farmers' children across these countries annually in public elementary or secondary schools, thereby enhancing families' prospects of breaking free from poverty.

Moreover, recognizing and addressing the pervasive gender gap in technology adoption within each nation emerges as a critical consideration. A strategic initiative to bridge this gap has the potential to reach an additional 810,200 to 1.8 million women farmers growing the top five crops, unlocking an estimated USD 80.7 million to USD 181.8 million in added revenue for this demographic. This two-pronged strategy – closing both the AI and gender adoption gaps – not only assures economic growth but also addresses vital socio-economic disparities within the agricultural landscape of SSA.

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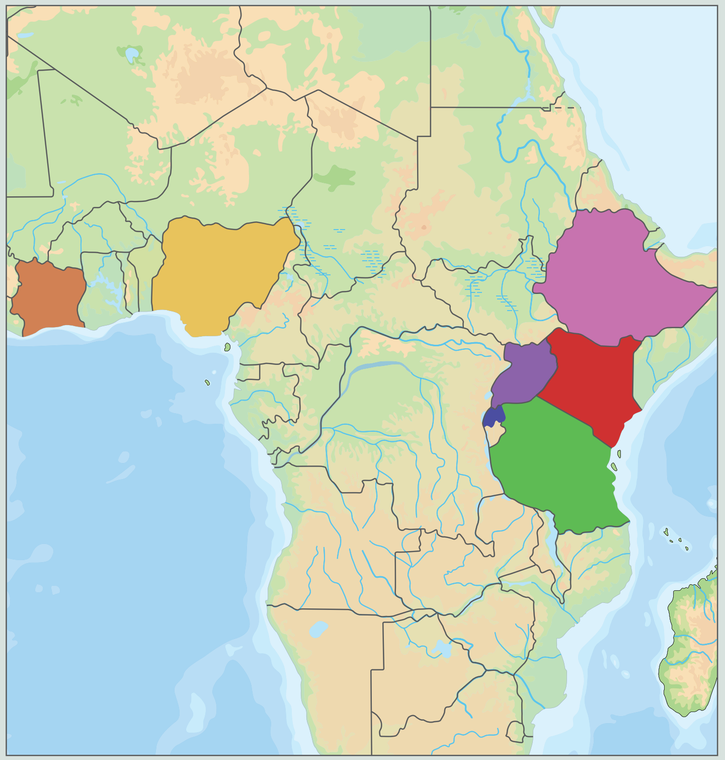


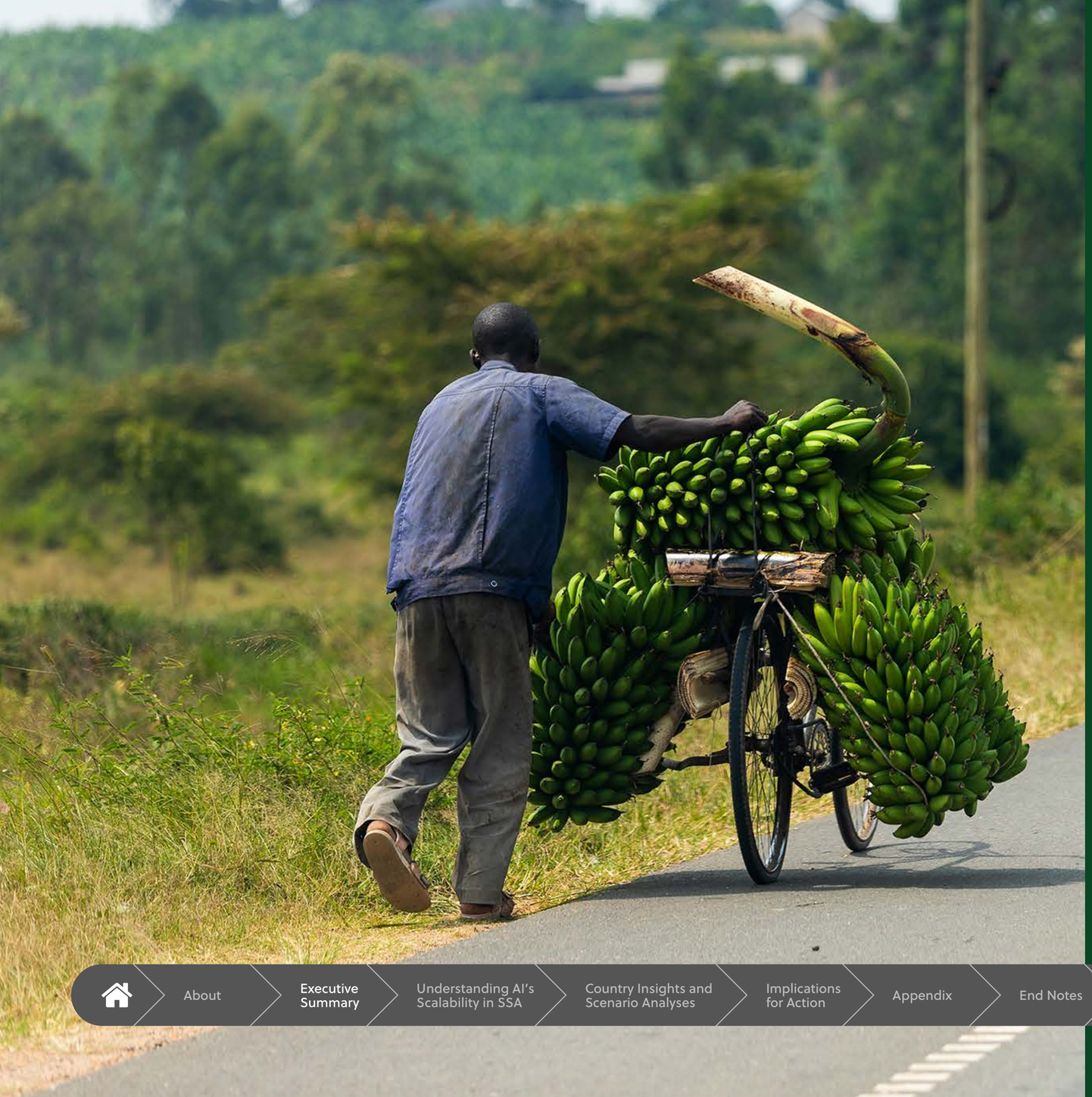
6.1 Billion USD in projected surge in revenue

1.5 Billion USD in direct revenue to SHFs

8.9 Million Children of SHFs can get an additional year of education

14 Million Smallholder farmers benefitted

4.9 Million Women farmers benefitted



1.8 million

additional women SHFs in SSA growing the top five crops can adopt AI for agriculture if the gender gap in digital adoption is closed.

5.3%

average gender gap in digital adoption in SSA.

USD 181.8 million

in additional revenue increases benefiting women SHFs in SSA if gender gap is closed.

Implications for Action

Increase Rural Electrification

Explore partnerships with standalone electricity providers, exemplified by companies like *Husk*, to introduce sustainable solutions in areas with underdeveloped or absent grids.

Deploy power banks to supplement electricity supply in regions facing intermittent power availability.

Improve Internet Access

Prioritize initiatives aimed at improving internet access, particularly in remote areas, to bridge the digital divide.

Develop targeted programs to address gender disparities in internet usage, ensuring inclusivity.

Advocate for increased competition within the telecommunication sector to drive down costs and enhance overall accessibility.

Expand Access to Smartphones

Implement financial measures, including tax reduction, subsidies, and small/microfinance loans, to enhance the affordability and accessibility of smartphones, with a focus on closing the gender gap.

Channel financial resources through established networks such as cooperatives, microfinance banks, and government-led MSME loan programs.

Enhance Functional Literacy

Provide comprehensive training programs for trusted intermediaries such as local extension workers and farmers' cooperative representatives, equipping them to effectively train and troubleshoot with farmers.

Empower stakeholders, including application developers and agronomists, to deliver impactful training sessions directly to farmers, individually or in groups.

Incorporate language translation features into applications, mirroring successful models like the incorporation of Microsoft-funded ChatGPT into WhatsApp in India,[11] to overcome language barriers and enhance user experience.

Foster Trust in Technology in Rural Communities

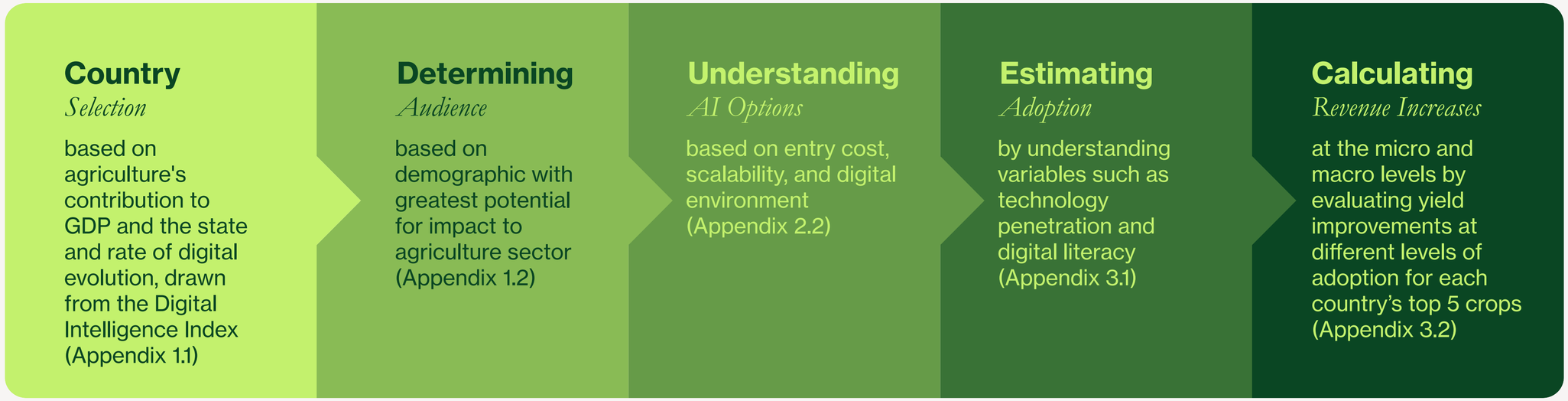
Acknowledge the skepticism that rural residents hold towards novel and unfamiliar technologies. Farmers are more open to advice from familiar and trusted sources. As such, engage local extension workers, community representatives, and farmer cooperatives in targeted marketing initiatives around Crop AI tools.

Develop a Vibrant AI Culture

Forge collaborative partnerships with local NGOs and foundations specializing in coding education for young talent. For instance, establish strategic alliances, akin to the Happy Coders Academy of Global Partnership for Education[12] or associations with NGOs like Pearls Africa Foundation,[13] to drive a culture of AI adoption.

Conduct hands-on training programs involving technologists, agronomists and crop protection experts, utilizing local crop imagery for the development of tailored treatment recommendations.

Methodology



80%

of the total annual food production in Sub-Saharan Africa is by smallholder farmers[14]

50%

of crops are lost annually to plant pests in Sub-Saharan Africa.[15]

USD 200 billion

is lost annually in Sub-Saharan Africa due to pests and diseases.[16]

Understanding AI's Scalability in SSA

Why Smallholder Farmers?

Smallholder farmers (SHFs) make up 80% of producers in SSA[17] and produce 80% of Africa's annual food production.[18] Treating this demographic as a priority for AI interventions would maximize the positive impact technology can have on both food production and economic gains. This approach would boost food security and guarantee that the economic benefits of embracing AI technology are distributed from the base of the pyramid upwards, thereby benefiting the entire economy.

Why Crop Protection AI?

In our study, we deliberately focus on AI applications that present the lowest barriers to adoption for smallholder farmers (SHFs). Our emphasis is on leveraging AI solutions that effectively utilize the resources available to SHFs while requiring minimal financial investment.

After a careful analysis of the most common agricultural AI applications (as seen in Appendix 2.2), we decided to center our study around disease detection algorithms, which are the most effective and scalable AI applications for our target demographic. These applications only require a smartphone, and they are a stellar solution because of their use of technology that is at scale and readily accessible to farmers.

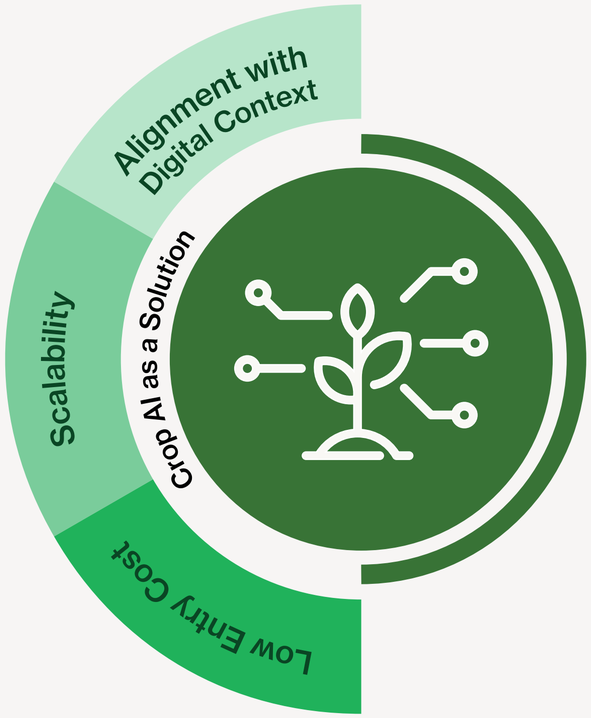
In this report, when we refer to AI, it exclusively pertains to applications contributing to crop loss reduction through crop diagnosis and protection. Image recognition technology, exemplified by apps like Plantix, exhibits remarkable capabilities in detecting diseases, boasting a 93% accuracy rate across over 82 plant species.[19] This technological advancement holds the potential to significantly diminish crop losses attributed to preventable diseases, all while requiring little to no financial investment from farmers in possession of a smartphone.

The urgency of deploying such AI solutions becomes even more apparent when considering that globally, up to 40% of crops are lost to pests yearly.[20] This figure is notably higher in Sub-Saharan Africa, 50%, where adoption of modern anti-pathogen agricultural techniques and resources is yet to be widespread.[21] David Chikoye, the Director of Plant Production & Health Management at the International Institute of Tropical Agriculture (IITA) estimates annual losses in SSA due to pests and diseases at a staggering USD 200 billion.[22] Thus, advocating for Crop Protection AI is an economically feasible solution to a devastating agricultural challenge.

Advocating for Crop Protection AI is an economically feasible solution to a devastating agricultural challenge.

The following framework helps us understand what the must-haves are for these kinds of targeted small AI interventions to make a large-scale impact in SSA.

Crop AI Adoption Checklist



Uses Readily Available Tech Resources

Scalable AI capitalizes on technology that is already available to SHFs. AI that takes advantage of the infrastructure already in place does not necessitate additional levels of trust, presents a relatively simple setup, and is quick to adopt.

Low to No Economic Investment

Some SHFs in SSA have limited economic resources, AI technology that is novel, complex, or requires new gadgets would be financially unviable. The ideal AI should require minimal or no economic investment to make sure that farmers can freely adopt it without being dissuaded or prohibited by cost.

Easily Acquirable

AI for SHFs should be easily acquirable in rural SSA markets. The ability of AI to penetrate the rural SSA market is very important; it implies that the product solves a challenge SHFs face and that it has struck a balance between the production cost and market price.

Low Barriers to Adoption

Wherever possible, AI for SHFs should simplify user engagement to compensate for low digital literacy. Presenting excessively complicated AI, although at times more beneficial for agricultural practices, risks having too steep a learning curve for the target demographic, which could lead to reduced uptake.

Stable Internet Connection

The most successful AI amongst SHFs would not need to rely on a stable internet connection. Many rural areas in SSA are yet to have reliable internet, and ensuring that AI can occasionally work offline increases the reliability and the likelihood that SHFs will use it.

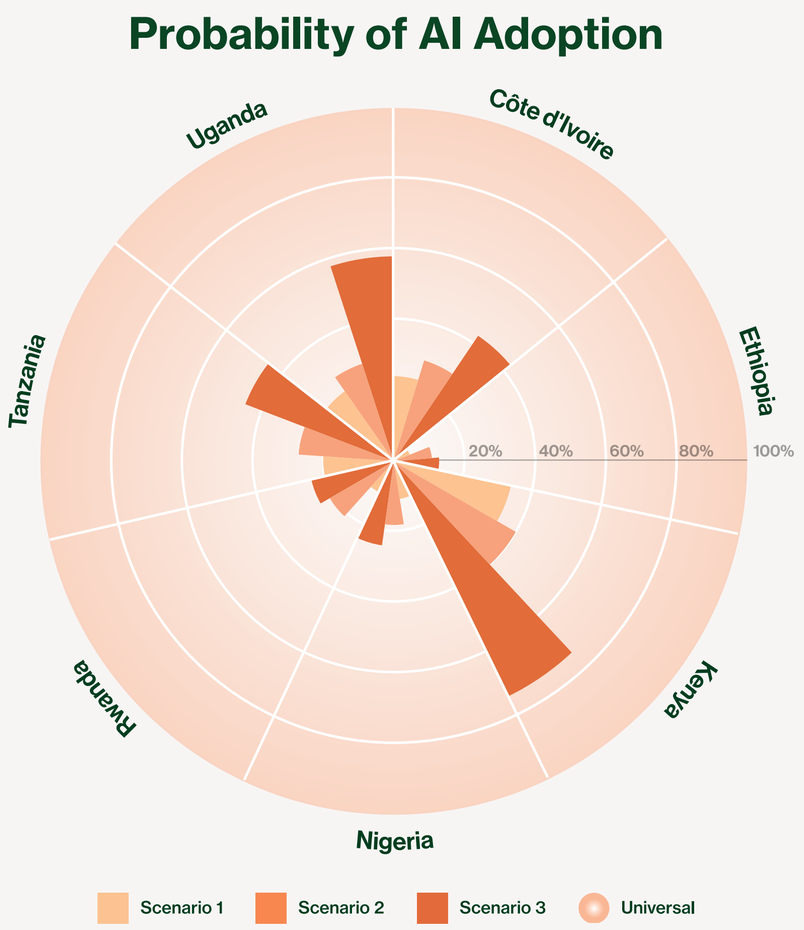
Estimating AI Uptake

Estimating Crop AI uptake requires an understanding of each country's technological resources and digital connectivity. By combining smartphone penetration with rural digital payments data, we have approximated what the probability of adoption would be for each country under three scenarios (as seen in the table below).

The first scenario, colored in light orange, reflects the country's current reality (or "status quo") by demonstrating the percentage of SHFs who will be early adopters of AI. The second and third scenarios (in medium orange and dark orange, respectively), are hypothetical, as they demonstrate how AI uptake can increase from the status quo if policymakers focus on removing barriers to AI adoption.

In all three scenarios, we consider each country's reality to understand how policy interventions in AI and AI-adjacent areas can impact the likelihood of adoption. A more in-depth explanation of our approach to measuring the probability of adoption can be found in Appendix 3.1. Refer to the Country Policy Recommendation Matrix section for our analysis of country-specific policy priorities.

We consider each country's reality to understand how policy interventions in AI and AI-adjacent areas can impact the likelihood of adoption.



Country Insights and Scenario Analyses

Côte d'Ivoire

Ethiopia

Kenya

Nigeria

Rwanda

Tanzania

Uganda

Country Insights and Scenario Analyses

Côte d'Ivoire

17%

agricultural contribution to Côte d'Ivoire's GDP[23]

45%

Côte d'Ivoire's labor force works in the agriculture sector[24]

3+ million

smallholder farmers live in Côte d'Ivoire[25]

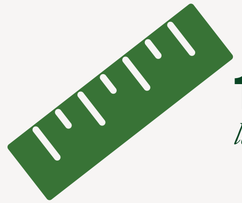
Côte d'Ivoire

Country Summary

- Côte d'Ivoire boasts the third largest economy in West Africa.[26] Approximately 75% of the national territory is comprised of arable agricultural land.[27] The agricultural sector plays a pivotal role, generating approximately 80% of total export earnings.[28]
- The majority of agricultural activities take place on small-scale farms, where traditional methods are employed. A significant proportion of farm leaders (72%) lack literacy, and only a minimal percentage (0.95%) of farms use tractors, while 4.4% utilize animal traction. It is noteworthy that 18% of these farms are overseen by women.[29]

8/10 *farmers in Côte d'Ivoire are smallholders*[33]

85% *of the arable land is cultivated by SHFs*[34]



1.3 ha *is the mean landholding capacity of SHFs*[35]

138th */193 in the AI Government Readiness Index*[36]

RANK

137*th*
138*th*
139*th*

- With 46% of the population below the poverty line,[30] the agricultural sector employs a significant portion of this demographic. Due to the detrimental effects of climate change, an estimated 1 million more people in the country could be driven into poverty by 2030, marking a potential increase of 2% to 6% in households facing extreme poverty[31] and vulnerable to food insecurity.
- Côte d'Ivoire ranks 95th out of 113 countries in the Global Food Security Index.[32]

AI Landscape

Côte d'Ivoire is in the early phases of developing AI, with concerted efforts to establish an innovative ecosystem featuring over 20 hubs,[37] including *seedspace*[38] and *jokkolabs*.[39] Initiatives like SADA (Smart Africa Digital Academy) and AReg4DT (Agile Regulation for Digital Transformation Program) underscore the country's commitment to promoting digital skills.[40]

In the agricultural sector, the adoption of digital technology in Côte d'Ivoire is not a recent phenomenon, as evidenced by initiatives like the AgriDI project in West Africa. This project has played a pivotal role in advancing e-agriculture, establishing a platform for the dissemination of information on effective farming practices through digital channels.[41]

Moreover, Côte d'Ivoire has engaged in AI experimentation, utilizing artificial neural networks to monitor riverine water and employing the random forest method to forecast sugarcane production. This involves the analysis of rainfall data, temperature data, and sugarcane yield data, contributing to the enhancement of agricultural practices.[42]

Economic Impact of Crop Protection AI Adoption

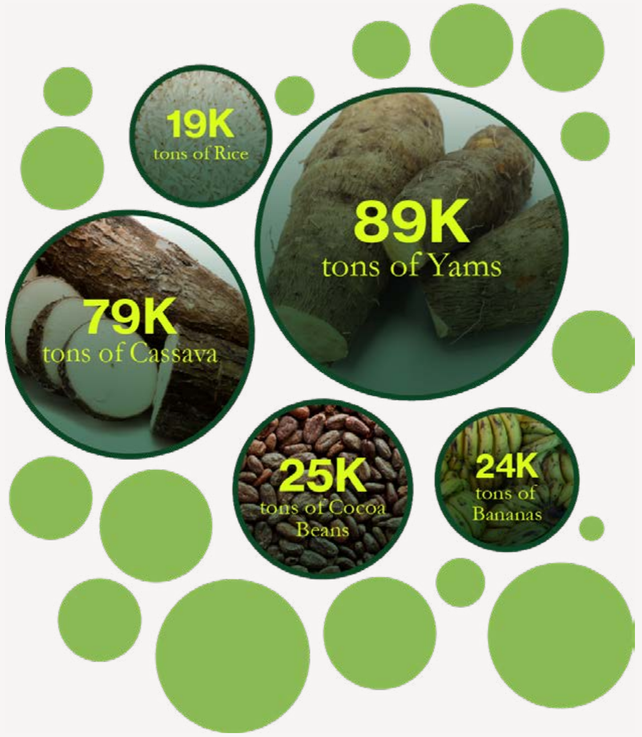
Economic Implications of Crop Protection AI Early Adopters (Scenario 1)

An estimated one-fourth of Smallholder Farmers (SHFs) cultivating the top five crops, equivalent to more than 369,700 Ivorian farmers, are currently well-positioned to adopt this AI technology.

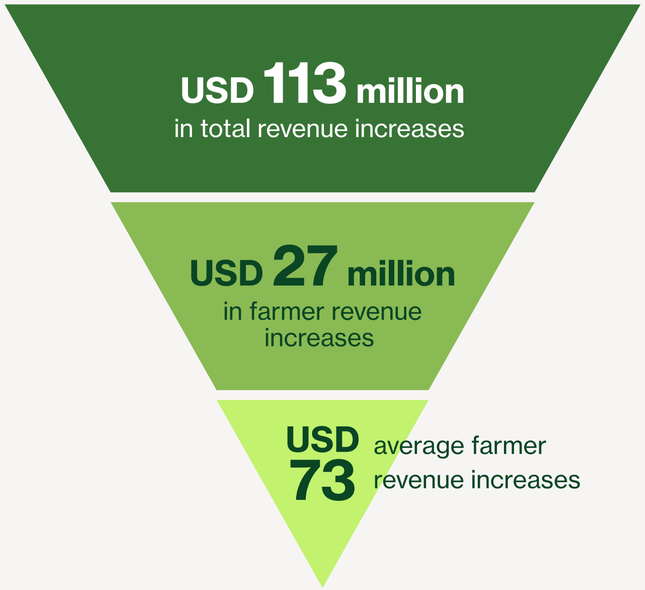
Given the prevailing state of digital literacy among rural communities, this anticipated adoption is expected to yield USD 27.1 million in additional revenue for these farmers, averaging USD 73 in extra revenue per farmer per planting cycle. While this sum might not seem significant, it amounts to an additional year of educating an elementary school child,[43] implying that even these marginal gains have the potential to change livelihoods.

Looking at the macro picture reveals even higher gains for the whole economy. The impact early adopters would have on the economy as a whole would produce roughly USD 113.1 million in revenue gains spread amongst actors in the agricultural value chain, further cementing the impact of AI uptake.

Gross yield improvement
resulting from AI use



Yield improvement and economic implications of crop AI adoption
by early adopters (Scenario 1)



Another significant impact of the increase in productivity spurred by AI adoption is the subsequent increase in food security. If 24% of farmers of the top five crops use AI to prevent diseases, they can contribute thousands of tons to the national food supply. Yam production would see an 89,100-ton increase, cassava would go up by 79,000 tons, and so on, as illustrated in the gross yield improvement visual.

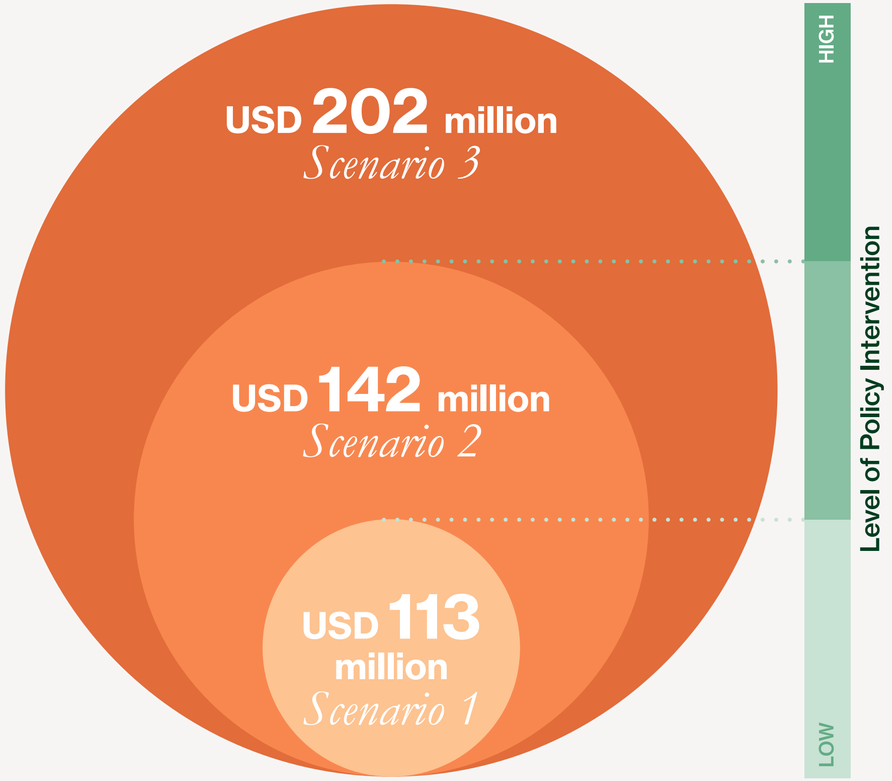
Economic Implications of Policy Interventions Buoying AI Adoption (Scenario Analyses)

The following six policy recommendations can facilitate SHFs' adoption of AI and increase revenue gains across the entire economy:

- Increase Rural Electrification
- Improve Internet Access
- Expand Access to Smartphones
- Enhance Functional Literacy
- Foster Trust in Technology in Rural Communities
- Develop a Vibrant AI Culture

Economic implication of crop AI adoption

Under three adoption scenarios



Through light policy intervention (as envisioned in scenario 2), which we predict spurs a 30% SHFs adoption rate (6% increase from scenario 1), AI uptake could impact an additional 94,600 SHFs. This would lead to a revenue increase of USD 142.1 million for the entire country, USD 34.1 million of which would benefit SHFs directly.

Furthermore, if the policymakers pursue rigorous policy intervention (scenario 3), we project a total of 43%, or 660,200 SHFs growing the top five crops, will adopt the technology. Revenue gains in this scenario are considerably bigger given the amount of people impacted. Instead of the USD 113.1 million economy-wide increase captured if only early-adopters use AI without policy intervention, this number would increase to USD 202 million, of which USD 48.5 million would be exclusively for farmers.

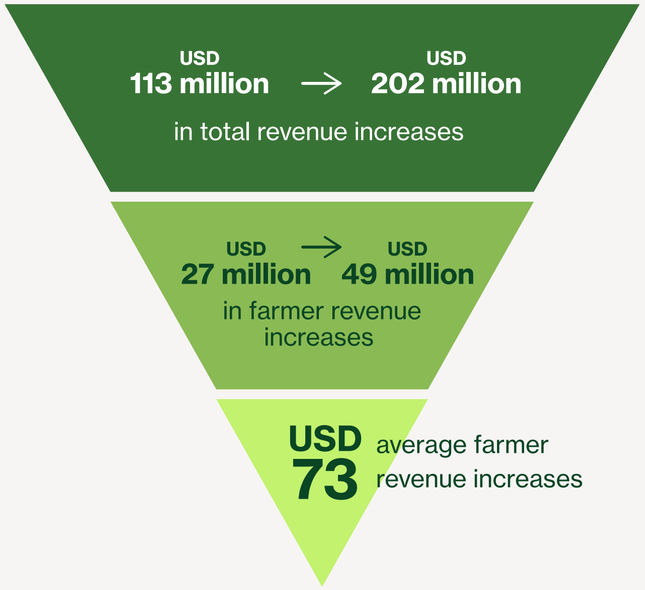
The previous visual (page 24) demonstrates how increasing adoption through targeted policy intervention can more than double economy-wide revenue improvements.

Economic Impact of AI Adoption Across the Three Scenarios

Approximately 0.16% to 0.29% GDP increase. The implementation of Crop AI across the top five cultivated crops is poised to contribute approximately 0.16% to 0.29% to the GDP, translating into an additional revenue range of USD 113.1 million to USD 202 million. This newfound revenue, dispersed across the food production and distribution value chain, is anticipated to have a direct impact on countless households.

Approximately 0.96% to 1.74% boost to the agricultural sector. Moreover, the introduction of Crop AI across the top five crops could result in a substantial 0.96% (in scenario 1) to 1.74% (in scenario 3) increase in the contribution of agriculture, fishery, and forestry to the overall economy.

Potential value creation
from policy interventions

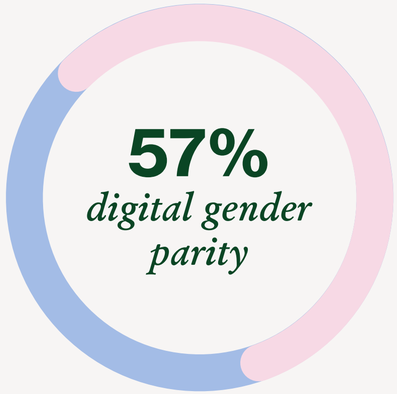


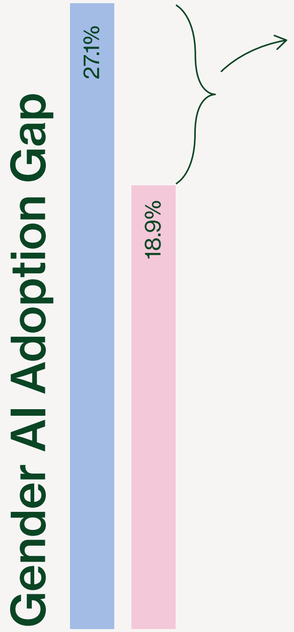
Bridging the Gender Gap

Our analysis reveals an 8-percentage point gender gap in AI adoption, with distinctions between women and men Ivorian farmers. To approximate this number, we built upon our *Progress to Digital Parity Study*, which benchmarks Côte d'Ivoire's progress in bridging the digital gender divide and achieving an inclusive digital economy for all. The methodology for this analysis can be found in Appendix 3.3.

Despite women constituting 36% of farmers,[44] our projections indicate that only 105,600 out of the estimated 559,500 women farmers growing the top five crops are likely to be early adopters. Addressing this gender digital gap holds the potential to spur a significant advancement in Crop AI adoption.

Furthermore, taking concerted steps to bridge the gender adoption gap could have a positive impact on an additional 45,900 women SHFs actively engaged in the cultivation of the top five crops. This dedicated effort has the potential to generate USD 3.4 million in additional revenue exclusively for these women, signifying a meaningful step toward gender-inclusive technological adoption in agriculture.





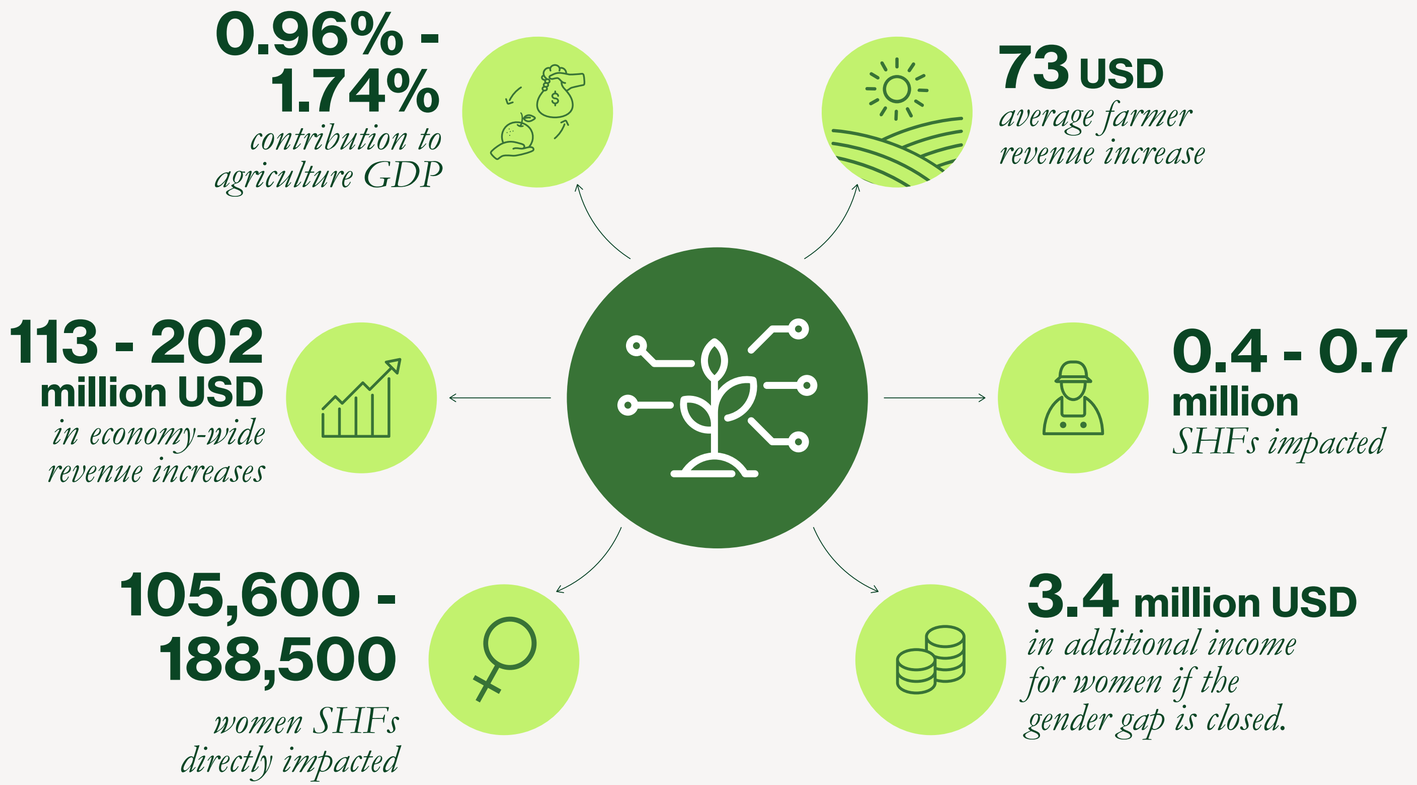
8.2%
gender adoption gap in AI

45,900
additional women smallholder farmers

USD 3.4 million
in additional income generated

Despite women constituting 36.4% of farmers, our projections suggest that only 105,600 out of the estimated 0.5 million female farmers 18.9% are likely to be early adopters.

Economic Impact Summary



Country Insights and Scenario Analyses

Ethiopia

38%

agricultural contribution to Ethiopia's GDP[45]

64%

of Ethiopia's labor force works in the agriculture sector[46]

4.1 million

smallholder farmers growing the top five crops in Ethiopia

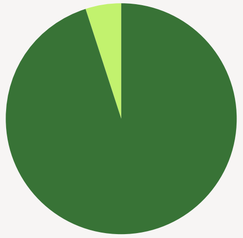
Ethiopia

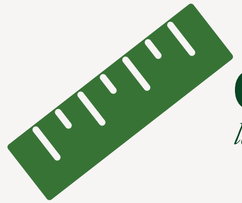
Country Summary

- Agriculture is the predominant occupation for Ethiopian smallholdings, with on-farm income making up 79% of their total earnings. Crop production is the most common form, representing 62% of these agricultural activities.[47]
- Crop productivity is considerably influenced by climate variability, including droughts and pests.
- Ethiopia is a drought prone country. SHFs, who normally rely on rainfall for farm irrigation, are particularly vulnerable to food insecurity resulting from volatile weather patterns. This also impacts their livelihoods: approximately 80% of Ethiopians in rural areas depend on agriculture for income, earning less than a dollar per day.[48]
- Ethiopia ranks 100th out of 113 countries in the Global Food Security Index.[49]

7/10 *farmers in Ethiopia are smallholders*[50]

95% *of food produced in Ethiopia is by smallholder farmers*[51]





0.8 ha *is the mean landholding capacity of SHFs*[52]

140th */193 in the AI Government Readiness Index*[53]

RANK

139*th*
140*th*
141*th*

AI Landscape

The Ethiopian Agricultural Transformation Agency (ATA) has spent various years improving digital infrastructure in rural areas, mapping and storing agricultural data, and empowering farmers with insights derived from their data collection.[54] These initiatives indicate a clear commitment to technological uptake, demonstrating that Ethiopian farmers are well poised to adopt AI in agriculture.

To solidify this momentum, the government of Ethiopia released Digital Ethiopia 2025, a plan that explicitly mentions the crux between AI and agriculture.[55] It identifies agriculture as one of the four main pillars that need to be developed in order to ensure digital transformation. The plan's purpose is to accelerate the ATA's work by identifying areas for improvement and defining the most important steps that need to be taken in order to reduce inefficiencies through AI implementation. These steps include guidelines for building a digital agriculture platform, supporting and incentivizing agritech entrepreneurship, amongst others.

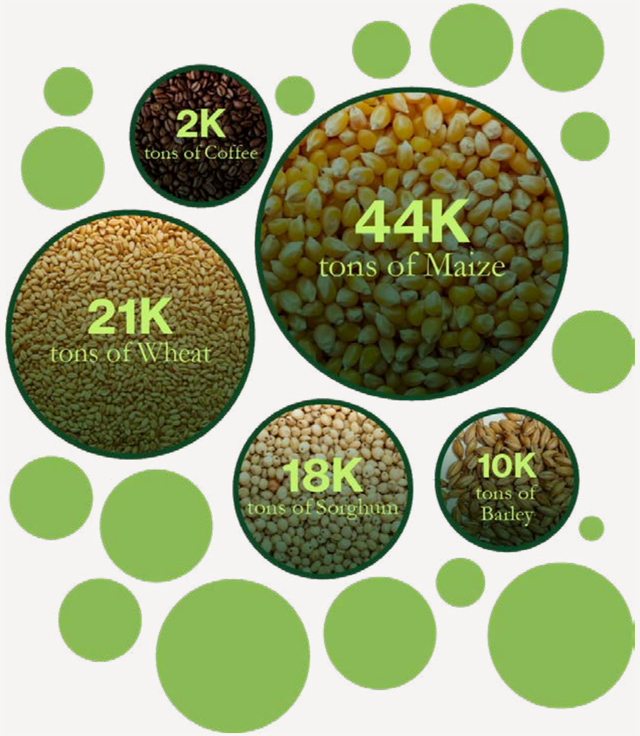
Economic Impact of Crop Protection AI Adoption

Economic Implications of Crop Protection AI Early Adopters (Scenario 1)

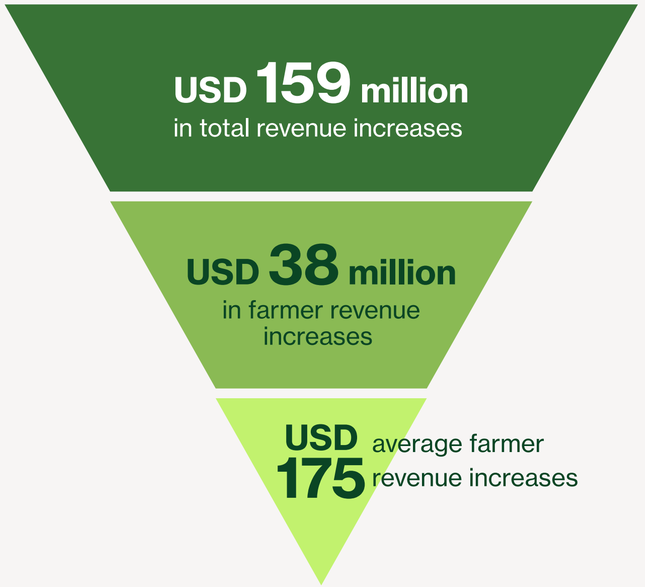
Under current circumstances, 5% of SHFs are projected to be early adopters of AI technology. This means that a total of 218,500 farmers are ready for this technology. We estimate there will be an increase of USD 38.2 million in farmer revenue as a result of AI adoption. At the individual level, this would be USD 175 per farmer per planting cycle. This represents the highest spike in farmer revenue from the countries examined in this study. An increase in revenue of this proportion would mean a significant change in the livelihoods of the poorer SHFs, improving the living conditions of many and making them food secure.

The economic gains do not stop at the farmer level; the additional crops circling in the foodstuffs economy would benefit many more actors in the agricultural supply chain, ranging from transporters to storers to sellers and more. We therefore project that early adopters' total impact on the Ethiopian economy would be roughly USD 159.2 million.

Gross yield improvement
resulting from AI use



Yield improvement and economic implications of crop AI adoption
by early adopters (Scenario 1)



Aside from the economic gains, AI technology would enable farmers to prevent crop loss and contribute to the region's food security. Among the top five crops in Ethiopia, using AI to diagnose crops would lead to a 43,700-ton increase in maize yield, 21,300-ton increase in wheat yield, 18,200-ton increase in sorghum, 9,600-ton increase in barley, and 1,900-ton increase in coffee, as described in the the visual in the previous page.

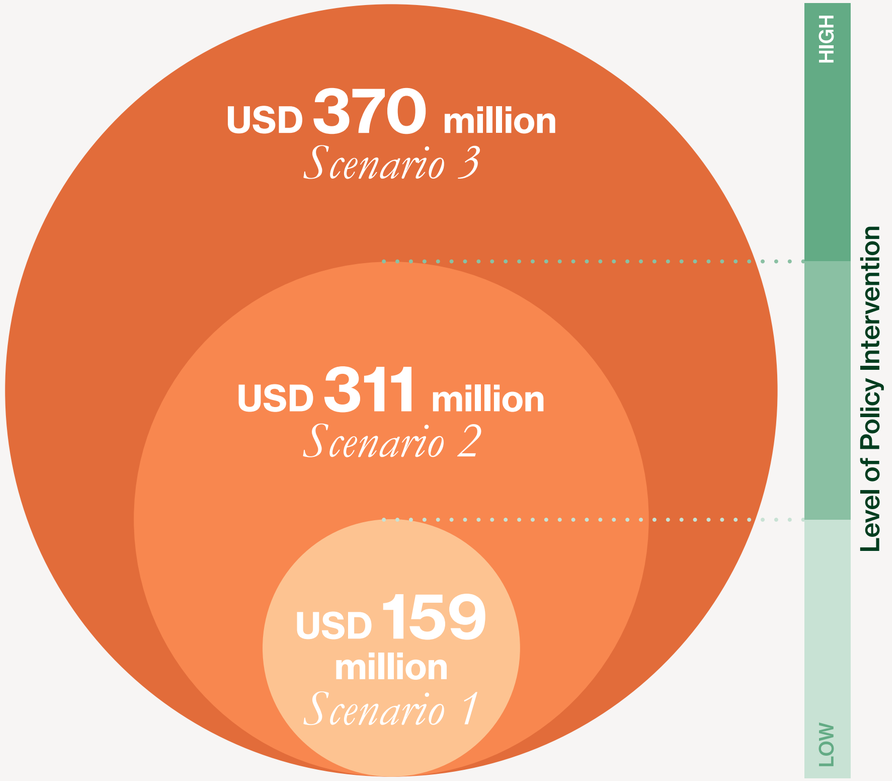
Economic Implications of Policy Interventions Buoying AI Adoption (Scenario Analyses)

The following six policy recommendations, if implemented, could expand the impact of AI technology beyond early adoption:

- Increase Rural Electrification
- Improve Internet Access
- Expand Access to Smartphones
- Enhance Functional Literacy
- Foster Trust in Technology in Rural Communities
- Develop a Vibrant AI Culture

Economic implication of crop AI adoption

Under three adoption scenarios



Scenarios 2 and 3 entail the implementation of the policy recommendations listed above, with the former assuming a more moderate policy implementation and the latter assuming a more rigorous and stringent approach.

In scenario 2, the adoption rate among smallholder farmers in Ethiopia would increase from 5% to 11%. This change is projected to result in total revenue gains, estimated to increase from USD 159.2 million to USD 311.2 million.

In scenario 3, the impact on farmer revenue and GDP is more pronounced due to a more stringent policy transformation, allowing for a broader uptake estimated to be at 13%. Although the increase from scenario 2 is not substantial, it still contributes to an overall rise in revenue, benefiting farmers with USD 88.9 million and boosting the economy by USD 370.3 million.

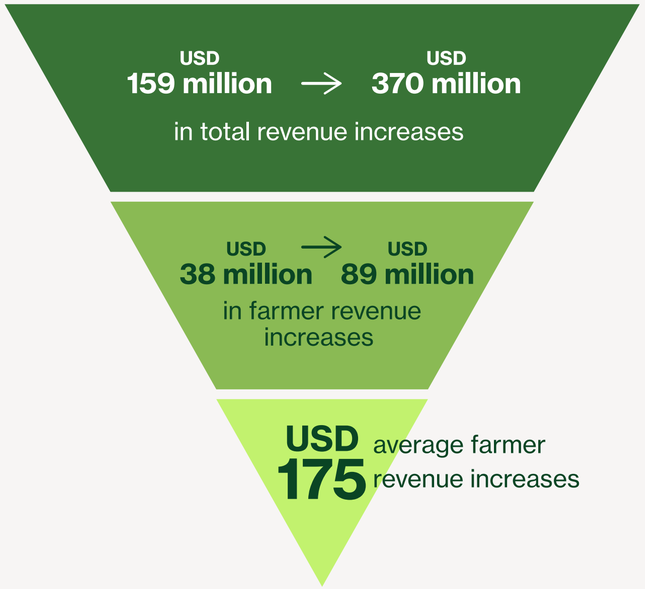
Economic Impact of Crop AI Adoption Across the Three Scenarios

Approximately 0.29% to 0.67% GDP increase. Deploying Crop AI across the top five cultivated crops in Ethiopia is projected to contribute approximately 0.29% to 0.67% to the GDP, resulting in an additional revenue range of USD 159.2 million to USD 370.3 million. This newfound revenue, distributed across the food production and distribution value chain, is estimated to directly impact countless households.

Approximately 0.77% to 1.78% boost to the agricultural sector. Introducing Crop AI across the top five crops could lead to a significant 0.77% to 1.78% increase in the contribution of agriculture, fishery, and forestry to the overall economy. Anticipating the impact at the farmer level, over 218,500 Ethiopian farmers engaged in cultivating the top five crops are deemed well-positioned to adopt this AI technology, considering the current state of digital literacy among rural dwellers.

The early adoption of AI holds the potential for a collective increase in farmer revenue by USD 38.2 million across all five crops. Furthermore, the potential for revenue improvement could more than double if a greater number of farmers can adopt AI technology through the implementation of policies recommended in this report.

Potential value creation
from policy interventions

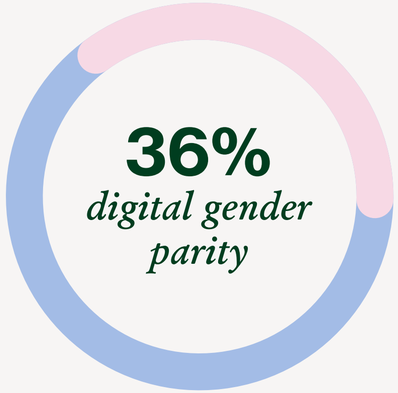


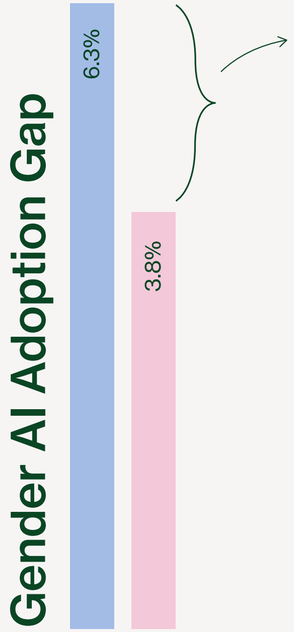
Bridging the Gender Gap

Our estimation reveals a 2-percentage point gender gap in AI adoption between women and men Ethiopian farmers. To approximate this number, we built upon our *Progress to Digital Parity Study*, which benchmarks Ethiopia's progress in bridging the digital gender divide and achieving an inclusive digital economy for all. The methodology for this analysis can be found in Appendix 3.3.

Despite women constituting 36% of farmers,[56] our projections suggest that only 56,300 out of the estimated 1.5 million women farmers growing the top five crops are likely to be early adopters. Addressing this gender digital gap has the potential to instigate a significant advancement in Crop AI adoption in Ethiopian agriculture.

Bridging the gender adoption gap could have a positive impact on an additional 36,100 women SHFs actively engaged in the cultivation of the top five crops. This collective effort has the potential to generate USD 6.3 million in additional revenue exclusively for these women, marking a substantial stride towards gender-inclusive technological adoption in Ethiopian agriculture.





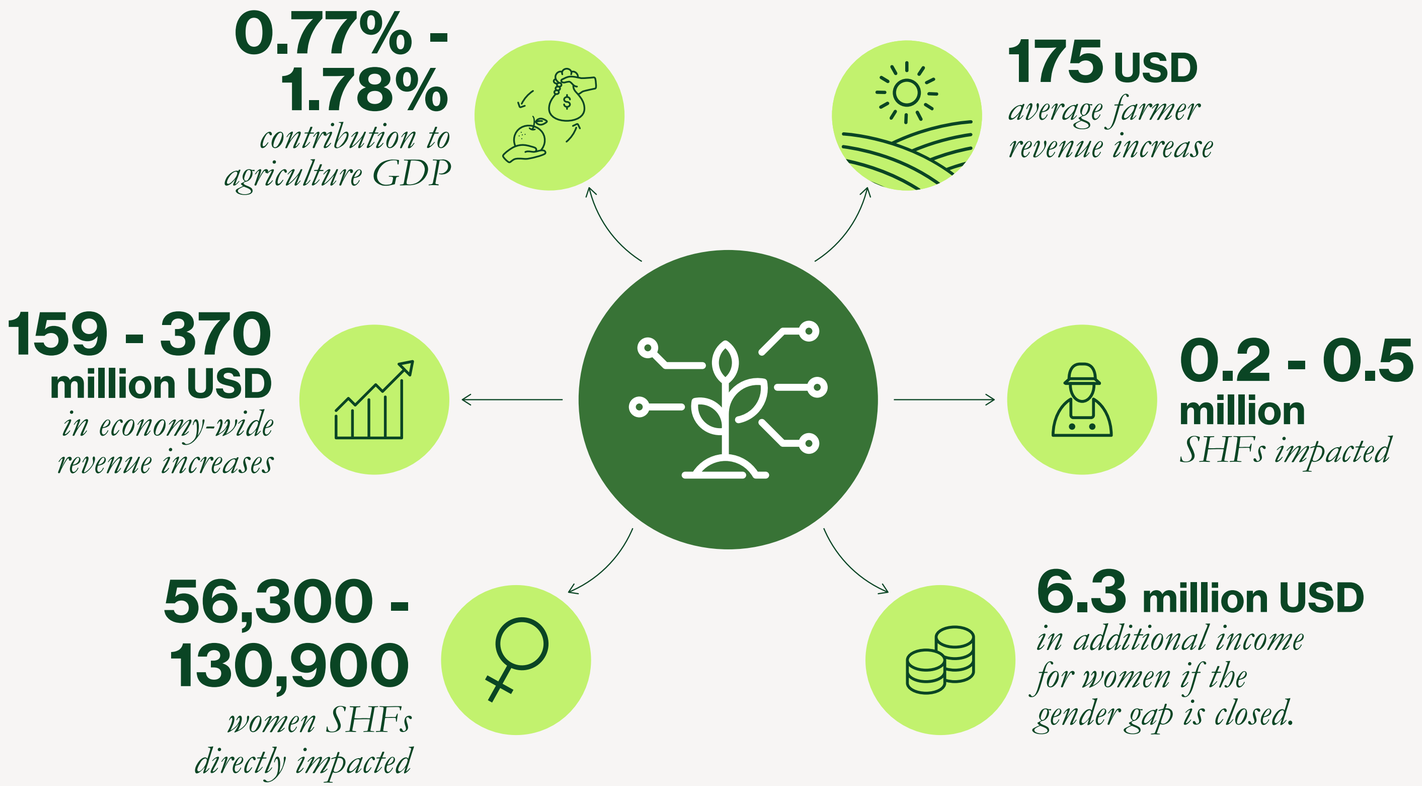
2.5%
gender adoption gap in AI

36,100
additional women smallholder farmers

USD 6.3 million
in additional income generated

Despite women constituting 36.3% of farmers, our projections suggest that only 56,300 out of the estimated 1.5 million female farmers 3.8% are likely to be early adopters.

Economic Impact Summary



Country Insights and Scenario Analyses

Kenya

21%

agricultural contribution to Kenya's GDP[57]

33%

of Kenya's labor force works in the agriculture sector[58]

7.5 million

smallholder farmers live in Kenya[59]

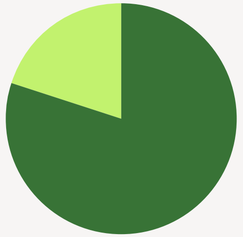
Kenya

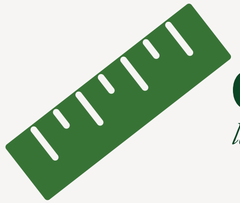
Country Summary

- The agriculture sector employs more than 40% of the total population and 70% of the rural population.[60] Export earnings from the sector account for 65% of total earnings.[61]
- It is estimated that over 30% of crops are lost due to diseases, pests, and weeds, posing a substantial threat to the sustainability of crop production in Kenya.[62] Moreover, only 20% of the land in Kenya is deemed suitable for farming, with the remaining 80% is categorized as arid.[63,64]
- 46% of Kenya's population lives on less than a dollar a day.[65] Additionally, 36.5% of the population faces food insecurity, and 35% of children under five years old experience stunting, indicating chronic malnutrition.[66]

8/10 *farmers in Kenya are smallholders*[70]

80% *of the arable land is cultivated by SHFs*[71]





0.5 ha *is the mean landholding capacity of SHFs*[72]

101st */193 in the AI Government Readiness Index*[73]

RANK

100*th*
101*st*
102*nd*

- Agriculture is the primary income source for the rural population.[67] In 2019, the World Bank reported households in Kenya solely involved in agriculture contributed 31.4% to the alleviation of rural poverty.[68]
- Kenya ranks 82nd out of 113 countries in the Global Food Security Index.[69]

AI Landscape

Kenya is a regional leader in fostering tech investment. The Vision 2030 plan,[74] for example, envisions the development of a new, prominent technology hub that can promote innovation and offer a favorable environment to investors.[75]

Evidence of multisectoral interest can be seen by private actors' longstanding investment in developing Kenya's AI capacities. IBM's AI Lab, for example, is celebrating 10 years since it first opened in Nairobi (the first of two labs in the entire continent).[76] Additionally, Kenya accounts for roughly a third of all SSA's agritech start-ups, and is one of the biggest destinations for tech investments in the region.[77]

Kenya is also making efforts to rally the economy around a collective approach to technological adoption. In 2018, the ICT Ministry established the Kenyan Task Force on Distributed Ledgers and AI. Its objective is to identify key areas where policymakers should encourage tech investment and advocate for regulations that promote economic development. It recommended the establishment of a National Digital Infrastructure to facilitate the adoption of AI in industries with high potential, such as agriculture.[78] The proposal outlines clear steps for integrating technology into various aspects of the supply chain, including land titling, fertilizer and seed distribution, food quality tracking, and, significantly for this report, utilizing AI to enhance yields through weather monitoring and agronomic advisory services.

Economic Impact of Crop Protection AI Adoption

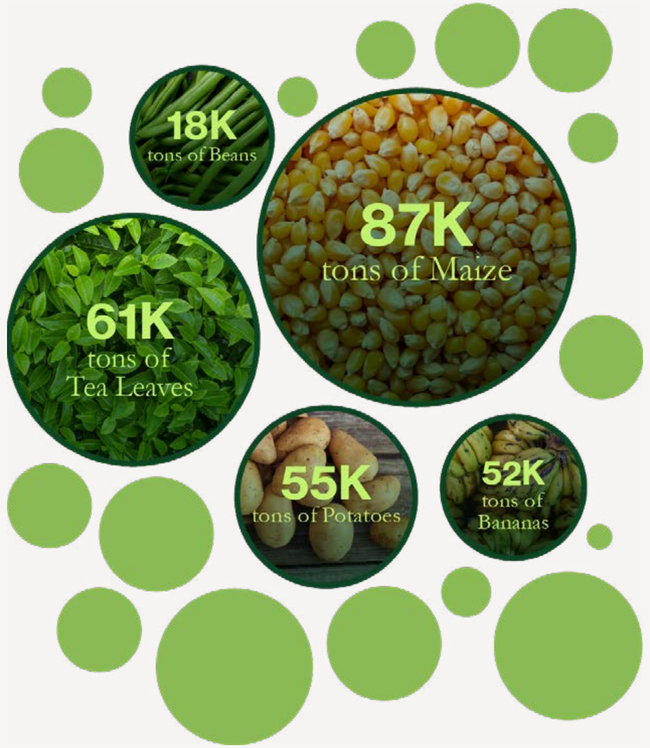
Economic Implications of Crop Protection AI Early Adopters (Scenario 1)

We anticipate that roughly 1 million Kenyan farmers, or 34% of SHFs growing the top five crops, will be early adopters of Crop AI. This is expected to generate USD 99.6 million in additional revenue for these farmers, averaging USD 97 per farmer per planting cycle. This additional revenue may seem small, but when taking Kenyan prices into consideration, it is the equivalent of covering the cost of sending a child to either public or private elementary school for a year.[79]

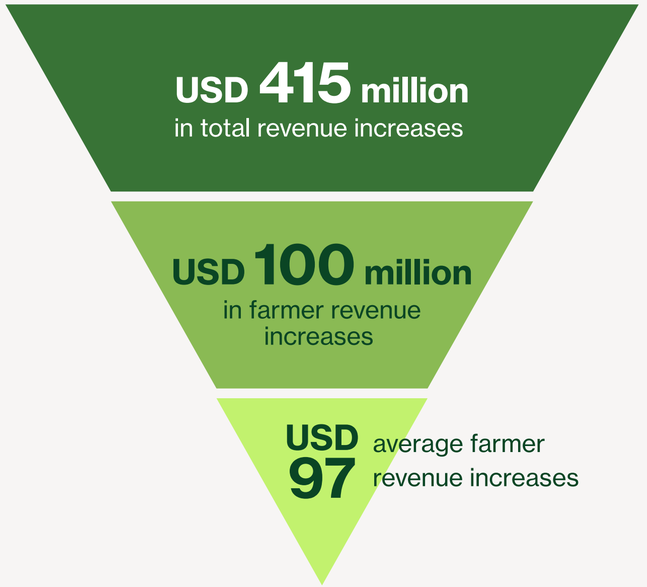
The revenue gains do not stop at the farmer level. AI uptake by the 1 million early adopters would lead to a USD 414.9 million increase in additional revenue for the whole economy, USD 99.6 of which benefits SHFs directly and USD 315.2 million of which would go to other actors within the Kenyan agricultural economy.

In addition to this economic benefit, the adoption of AI would produce significant strides in the fight against

Gross yield improvement
resulting from AI use



Yield improvement and economic implications of crop AI adoption
by early adopters (Scenario 1)



regional food security. We project that early adopters using AI to diagnose crop deficiencies could produce an additional 86,600 tons of maize, 61,300 tons of tea leaves, 55,300 tons of potatoes, 52,000 tons of bananas, and 17,500 tons of beans. This is all in the base scenario – the following section discusses the increase in revenue gains if policymakers were to intervene by fostering AI adoption.

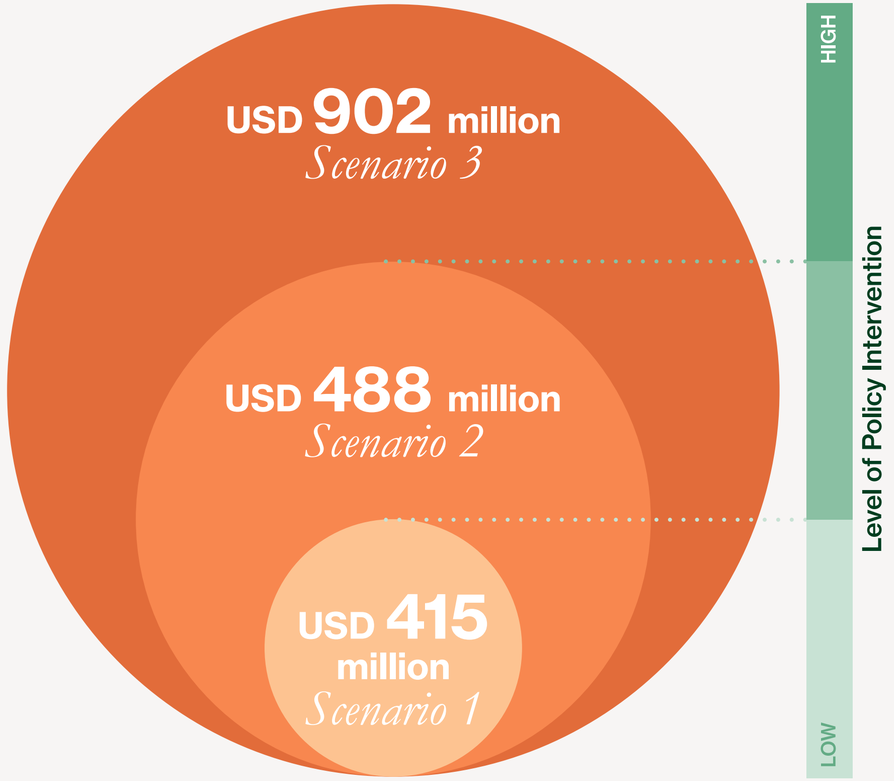
Economic Implications of Policy Interventions Buoying AI Adoption (Scenario Analyses)

The prospects for revenue improvement could more than double if more farmers can adopt AI technology through the implementation of policies recommended in this report:

- Increase Rural Electrification
- Improve Internet Access
- Expand Access to Smartphones
- Enhance Functional Literacy
- Foster Trust in Technology in Rural Communities
- Develop a Vibrant AI Culture

Economic implication of crop AI adoption

Under three adoption scenarios



Working on these policy recommendations, as we explain in detail in the policy implications section, can unlock significant gains for farmers and the rest of the economy. Through partial policy intervention, policymakers can increase the total revenue gains from USD 414.9 million in the base scenario to USD 487.8 million in scenario 2, which represents an increase from 34% in adoption to 40%. This would be particularly beneficial for farmers, given that their share of the increase would go from USD 99.6 million to USD 117.1 million.

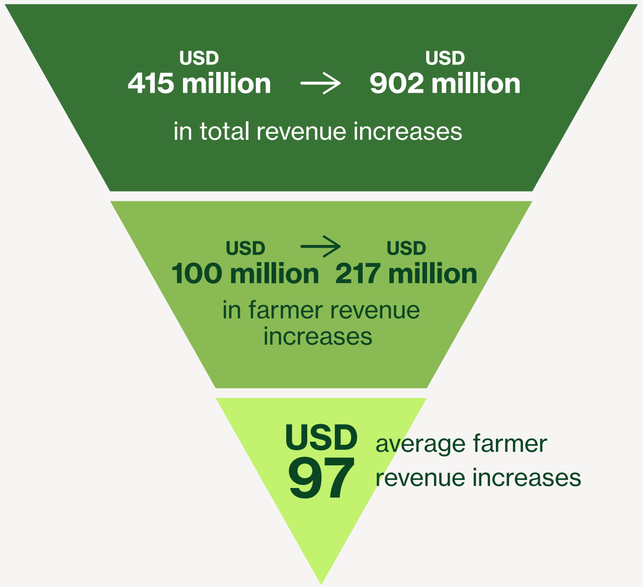
The revenue gains could be even higher if rigorous policy implementation (scenario 3) is pursued. Increasing AI adoption to 74%, as we expect would be the case through holistic policy interventions, would lead to an additional USD 487 million unlocked on top of the base scenario, for a total of USD 901.9 million across the entire economy.

Economic Impact of Crop AI Adoption Across the Three Scenarios

Approximately 0.73% to 1.59% GDP increase. Implementing Crop AI across the top five crops cultivated could contribute approximately 0.73% to 1.59% to the GDP, translating to an additional revenue of USD 414.9 million to USD 901.9 million. This newfound revenue, distributed across the food production and distribution value chain, is estimated to directly have an impact on thousands of households.

Approximately 3.44% to 7.5% boost to the agricultural sector. The introduction of Crop AI across the top five crops could lead to a notable 3.44% (scenario 1) to 7.5% (scenario 3) increase in the GDP contribution of agriculture, fishery, and forestry sector. This means that, depending on the rigor with which policies are implemented to increase AI uptake, anywhere between 1 million and 2.2 million SHFs can be positively impacted by revenue gains, the latter totaling roughly 74% of all SHFs farming the top five crops in Kenya.

Potential value creation
from policy interventions

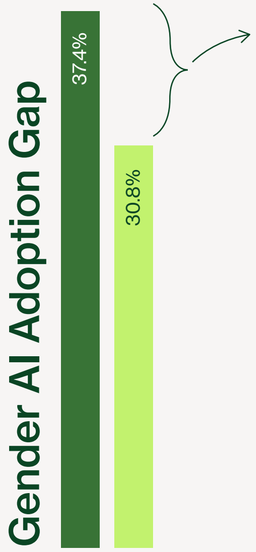


Bridging the Gender Gap

We project a 6-percentage point gender gap in AI adoption among Kenyan farmers. To estimate this number, we built upon our *Progress to Digital Parity Study*, which benchmarks Kenya's progress in bridging the digital gender divide and achieving an inclusive digital economy for all. The methodology for this analysis can be found in Appendix 3.3.

Despite women constituting 51% of farmers,[80] we anticipate that only 473,300 out of the estimated 1.5 million women farmers growing the top five crops are likely to be early adopters.

Bridging this gender digital gap holds the potential for a significant advancement in Crop AI adoption. Addressing the gender adoption gap can positively impact an additional 101,500 women SHFs engaged in cultivating the top five crops, generating USD 9.8 million in additional revenue exclusively for these women SHFs.



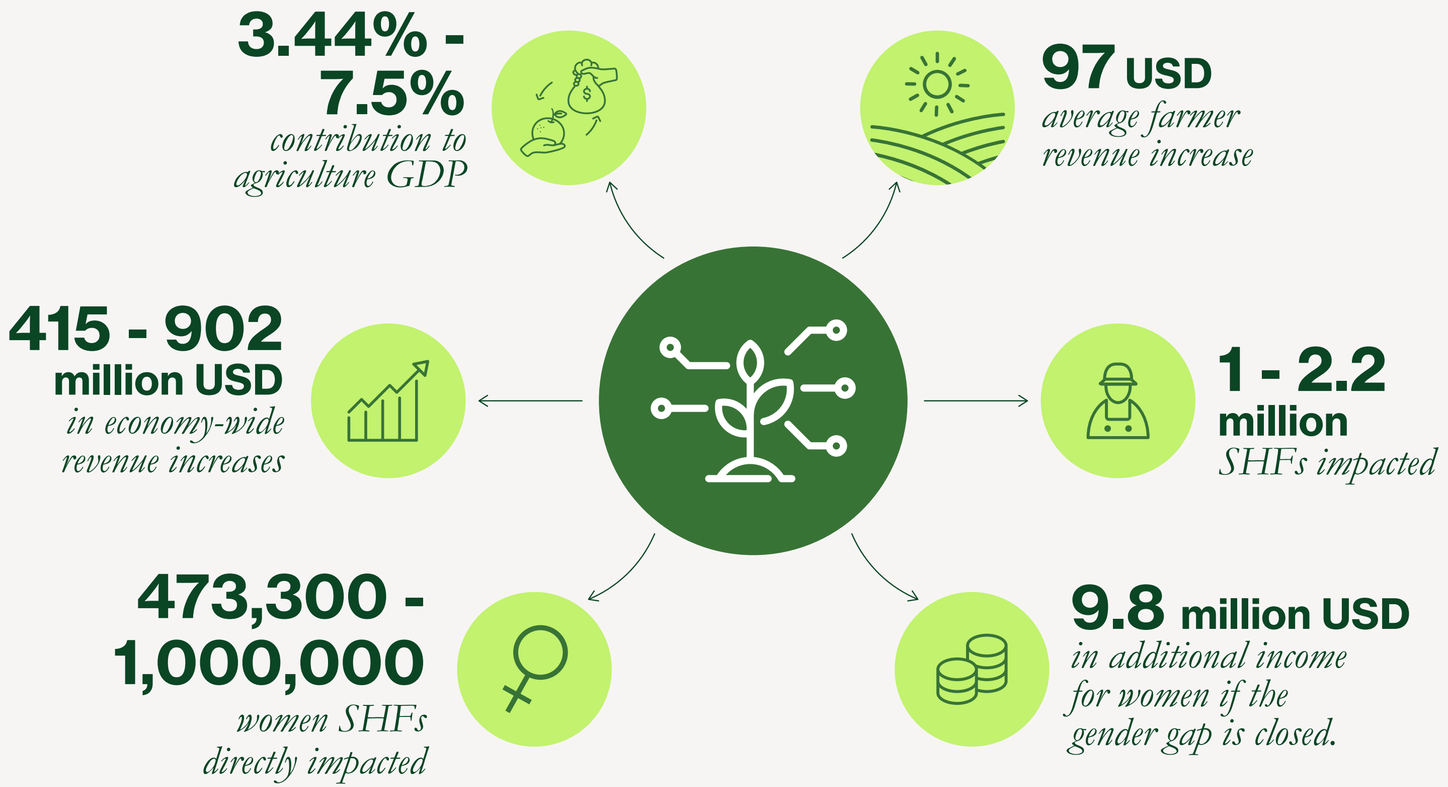
6.6%
gender adoption gap in AI

101,500
additional women smallholder farmers

USD 9.8 million
in additional income generated

Despite women constituting 50.8% of farmers, our projections suggest that only 473,500 out of the estimated 1.5 million female farmers 30.8% are likely to be early adopters.

Economic Impact Summary



Country Insights and Scenario Analyses

Nigeria

24%

agricultural contribution to Nigeria's GDP[81]

35%

of Nigeria's labor force works in the agriculture sector[82]

38 million

smallholder farmers live in Nigeria[83]

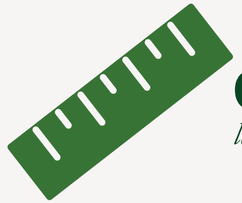
Nigeria

Country Summary

- Nigeria possesses 98.3 million hectares of land of which 74 million hectares are suitable for farming. However, only half of this farmable land is currently utilized.[84] With 36.9 million hectares of arable land and a growing domestic demand for food, Nigeria is seen as a country well-placed to benefit from agritech advancements.[85]
- Over the past two decades, Nigeria has experienced a rise in extreme temperatures, droughts, and floods. Rainfall has become more erratic and unpredictable, which poses challenges for the country's SHFs. Only 1% of farmers in Nigeria use artificial irrigation, meaning that their reliance on rainfall to grow crops has led to higher economic volatility and food insecurity.[86]

9/10 *armers in Nigeria are smallholders*[91]

90% *of food produced in Nigeria is by smallholder farmers*[92]



0.5 ha *is the mean landholding capacity of SHFs*[93]

103rd */193 in the AI Government Readiness Index*[94]

RANK

102nd
103rd
104th

- Over 50% of the population resides below the USD 1.90 a day poverty line, with the majority concentrated in rural areas.[87]
- Despite Nigeria's historical economic focus on agriculture, a prolonged dependence on petroleum led to a nearly 50% reduction in overall agricultural output from 2002 to 2014.[88]
- The current food shortage is estimated to cost the country USD 10 billion annually.[89] Nigeria ranks 107th out of 113 countries in the Global Food Security Index.[90]

AI Landscape

The Federal Ministry of Communication and Digital Economy launched the National Digital Economy Policy and Strategy (NDEPS), which is a 10-year plan that aims to guide digital development by outlining the most important pillars that must be developed in tandem in order to foster digitalization.[95] Artificial intelligence is among the 'Emerging Technologies' outlined in this broad document, though it does not take a central role.

A particularly important enforcing body of the NDEPS is the National Information Technology Development Agency (NITDA),[96] which houses the National Center for Artificial Intelligence and Robotics (NCAIR).[97] The Center is defined as a 'special purpose vehicle' dedicated to exploring AI and AI-adjacent innovative technologies, as outlined in the NDEPS.

Despite the lack of government specificity on the potential agricultural impact, Nigeria's technology company ecosystem indicates that there is quite a big push towards using technological tools as a means to modernize the sector. Preliminary investigations indicate that Nigeria's tech and AI start-up scene is amongst the most developed of the countries studied.[98]

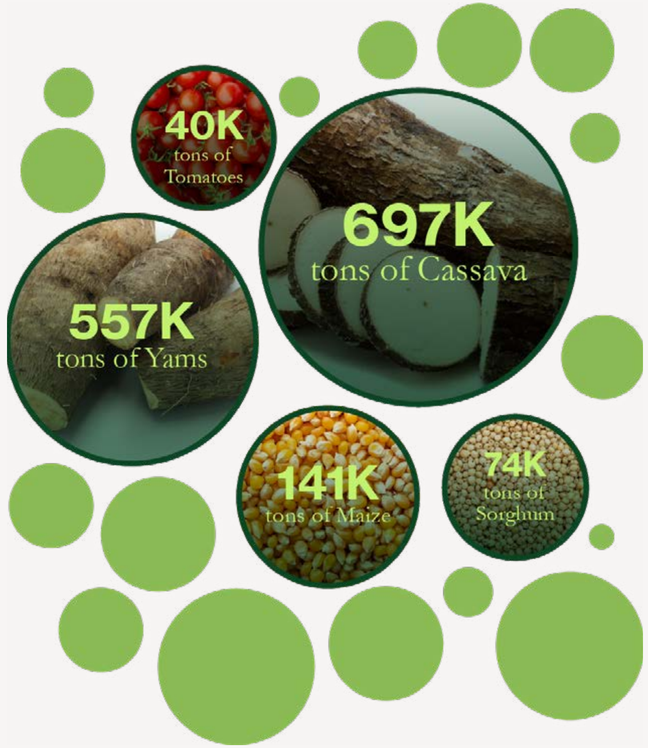
Economic Impact of Crop Protection AI Adoption

Economic Implications of Crop Protection AI Early Adopters (Scenario 1)

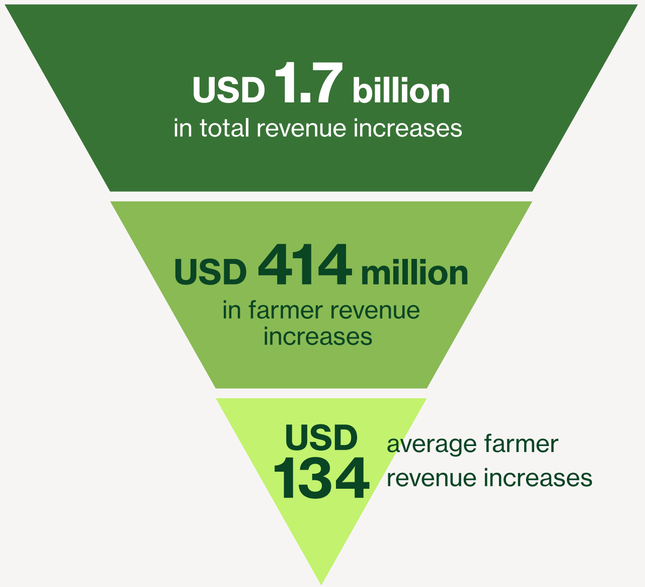
Maintaining the current digital infrastructure, approximately 3.1 million SHFs growing the top five crops are anticipated to be early adopters of AI technology (11%). This adoption leads to a USD 413.9 million revenue increase for SHFs, translating to an average of USD 134 in extra revenue per farmer per planting cycle. This significant rise in revenue is among the highest observed in the countries studied. The supplementary income could cover the tuition fees of an undergraduate student attending a Federal University, considering the substantial subsidies provided to Federal Institutions in Nigeria.[99]

The economic benefits do not stop at the farmer level; early adopters would be responsible for contributing USD 1.7 billion to the whole economy, 413.9 million of which would benefit SHFs directly. The rest would be distributed amongst actors in the agricultural economy value chain.

Gross yield improvement
resulting from AI use



Yield improvement and economic implications of crop AI adoption
by early adopters (Scenario 1)



Furthermore, early adoption benefits extend beyond financial gains, potentially lifting a substantial number of smallholder farmers out of food insecurity as well. The accompanying visual demonstrates notable increases in crop yields because of AI uptake. Cassava production is projected to increase by 696,500 tons, yams by 556,700 tons, maize by 140,800 tons, sorghum by 74,300 tons, and tomatoes by 39,500 tons.

Economic Implications of Policy Interventions Buoying AI Adoption (Scenario Analyses)

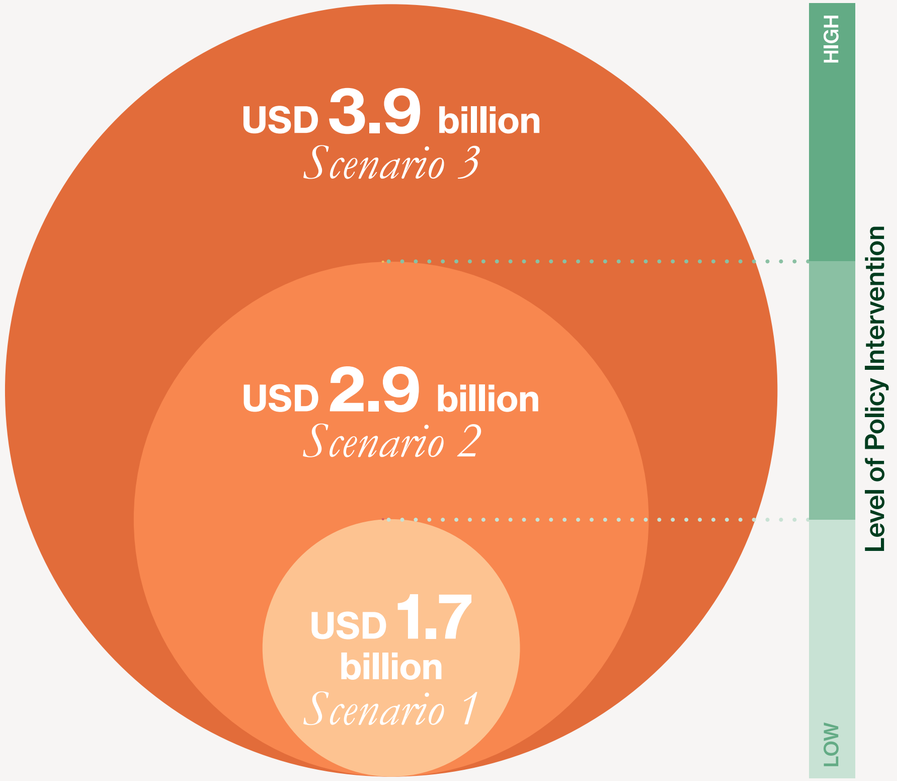
The following six policy recommendations, if implemented, could expand the impact of AI technology beyond early adoption:

- Increase Rural Electrification
- Improve Internet Access
- Expand Access to Smartphones
- Enhance Functional Literacy
- Foster Trust in Technology in Rural Communities
- Develop a Vibrant AI Culture

Policy interventions play a pivotal role in elevating the adoption rates and increasing revenue gains from AI adoption. For example, implementing policies, like the ones suggested above, to increase AI adoption from 11% (scenario 1) to 18% (scenario 2), could amplify revenue gains from USD 1.7 billion to USD 2.9 billion. These recommendations are essential for enabling farmers to access and integrate AI into their farming practices.

Economic implication of crop AI adoption

Under three adoption scenarios



Committing to even more rigorous and holistic policy implementation would lead to an adoption rate that surges to 24% (scenario 3). This underscores the imperative need for a substantial transformation in digital literacy and penetration. With such advancements, the projected revenue growth is estimated to soar from USD 2.9 billion to USD 3.9 billion, signifying a profound impact on the Nigerian economy.

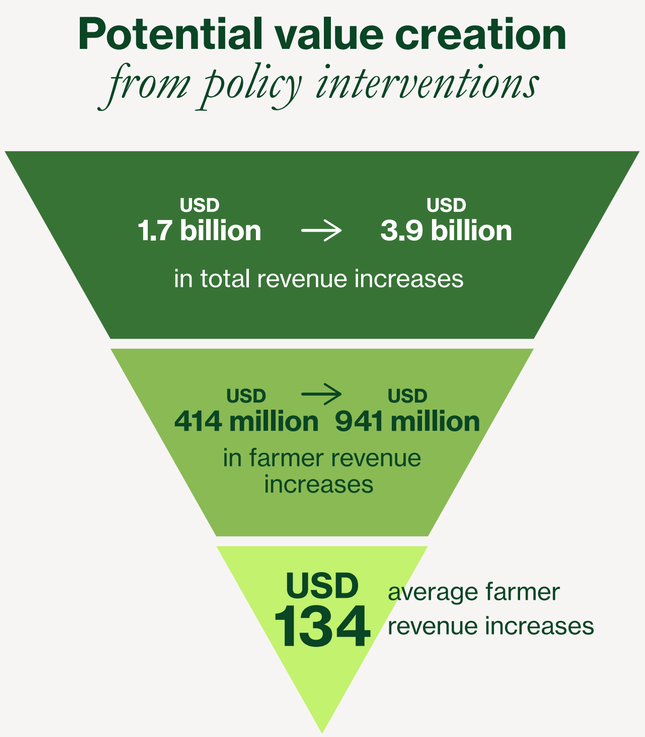
Economic Impact of Crop AI Adoption Across the Three Scenarios

Approximately 0.36% to 0.82% GDP increase. Deploying Crop AI across the top five crops holds the potential to contribute approximately 0.36% to 0.82% to the GDP or generate an additional revenue ranging between USD 1.7 billion to USD 3.9 billion. This substantial revenue boost, distributed across the food production and distribution value chain, is anticipated to directly impact millions of households, marking a transformative economic shift in Nigerian agriculture.

Approximately 1.52% to 3.46% boost to the agricultural sector. Introducing Crop AI across the top five crops could result in a notable 1.52% to 3.46% increase in the contribution of agriculture, fishery, and forestry to the overall economy. This demonstrates the significant potential for technological advancement to drive economic growth and sustainability in Nigeria's agricultural sector.

Our analysis anticipates that over 3.1 million Nigerian farmers actively engaged in the cultivation of the top five crops are well-positioned to embrace this AI technology, considering the prevailing state of digital literacy among rural communities. This anticipated adoption is expected to yield USD 413.9 million in additional revenue for these farmers, translating to an average of USD 134 in extra revenue per farmer per planting cycle.

The initial adoption of AI holds the potential for a collective increase in farmer revenue by USD 413.9 million across all five crops. Furthermore, the prospects for revenue improvement could increase by an additional USD 526.9 million if a greater number of farmers can adopt AI technology, facilitated by the implementation of policies recommended in this report.

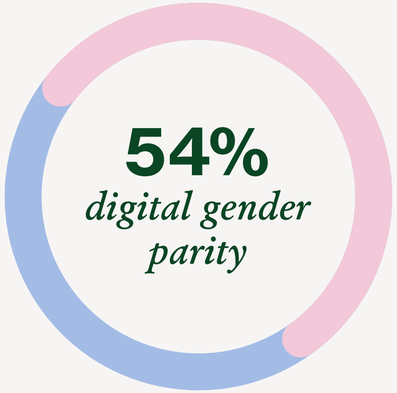


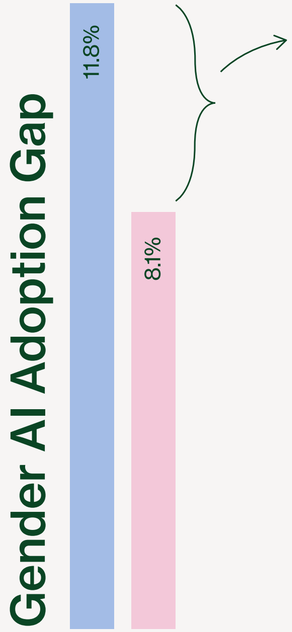
Bridging the Gender Gap

We have identified a 4-percentage point gender gap in AI adoption between women and men Nigerian farmers. To estimate this number, we built upon our *Progress to Digital Parity Study*, which benchmarks Nigeria's progress in bridging the digital gender divide and achieving an inclusive digital economy for all. The methodology for this analysis can be found in Appendix 3.3.

Despite women constituting 34% of farmers,[100] our projections indicate that only 804,200 out of the estimated 9.9 million women farmers growing the top five crops are likely to be early adopters of AI technology. Addressing this gender digital gap holds the potential to instigate a significant advancement in Crop AI adoption among Nigerian farmers.

Bridging the gender adoption gap can have a positive impact on an additional 370,900 women SHFs actively engaged in the cultivation of the top five crops. This concerted effort could generate USD 49.7 million in additional revenue exclusively for these women, providing a tangible economic boost to women farmers and contributing to overall gender equity in the agricultural sector.





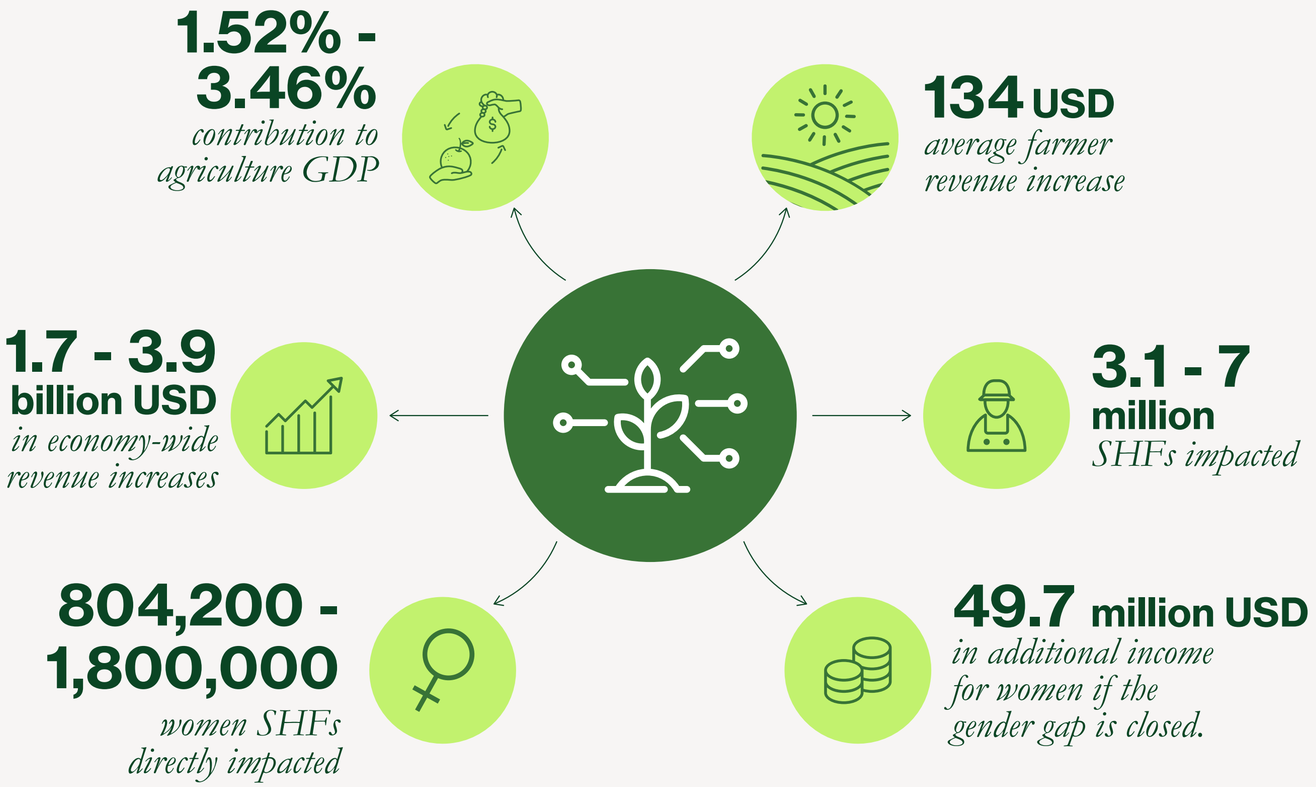
3.7%
gender adoption gap in AI

370,900
additional women smallholder farmers

USD 49.7 million
in additional income generated

Despite women constituting 34% of farmers, our projections suggest that only 804,200 out of the estimated 9.9 million female farmers 8.1% are likely to be early adopters.

Economic Impact Summary



Country Insights and Scenario Analyses

Rwanda

25%

agricultural contribution to Rwanda's GDP[101]

55%

of Rwanda's labor force works in the agriculture sector[102]

2.5 million

Rwandan smallholder farmers growing the top five crops

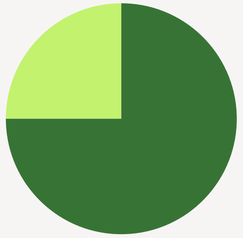
Rwanda

Country Summary

- The agricultural sector accounts for 31% of household income, and 52% of export earnings.[103]
- Agriculture serves as the primary economic activity in Rwanda, involving 70% of the population and employing around 72% of the working population.[104]
- Roughly 90% of Rwanda's land features slopes, posing challenges like soil loss, erosion, and reduced fertility. This makes agriculture susceptible to landslides and other natural impacts driven by weather changes. Rapid land degradation results in the annual loss of about 1.4 million tons of soil, translating to a financial loss of USD 320,000.[105]
- Approximately 38.2% of the population remains below the poverty line, and nearly one-fifth faces food insecurity.[106]
- Rwanda ranks 88th out of 113 countries in the Global Food Security Index.[107]

7/10 *farmers in Rwanda are smallholders*[108]

75% *of the agricultural production is by SHFs*[109]



0.4 ha *is the mean landholding capacity of SHFs*[110]

84th */193 in the AI Government Readiness Index*[111]

RANK

83rd
84th
85th

AI Landscape

Rwanda is a regional leader in identifying opportunities for technological uptake. Its latest macro-economic development plan, Vision 2050, for example, takes a step further than previous development efforts by focusing on the fostering of technology-intensive agriculture. It recognizes the importance of the private sector in the development of the agriculture industry. Thus, although the State has traditionally been at the center of the Rwandan agricultural economy's development, Vision 2050 sees the government's role turning into one of a "market enabler rather than a market actor."[112] Though AI is not explicitly mentioned in Vision 2050, the framing of the document implies that the government and private sector are favorable to the implementation of agritech and AI technologies.

Furthermore, Rwanda's start-up scene includes some promising ventures that can foster the growth and implementation of AI in agriculture. Currently, about 15% of tech start-ups based or operating in Rwanda are dedicated to agritech. An additional 26% are dedicated to fintech and DFS, which have been cited as crucial enablers for financing AI adoption at the SHFs level.[113] This is even more important considering that farms in Rwanda are, on average, quite small. Eight digital agricultural solutions are based in Rwanda, with roughly 3.5 million users. Additionally, 44 more solutions have a presence in the country.[114] Thus, Rwanda seems very well poised to reap the benefits of AI for agriculture.

Economic Impact of Crop Protection AI Adoption

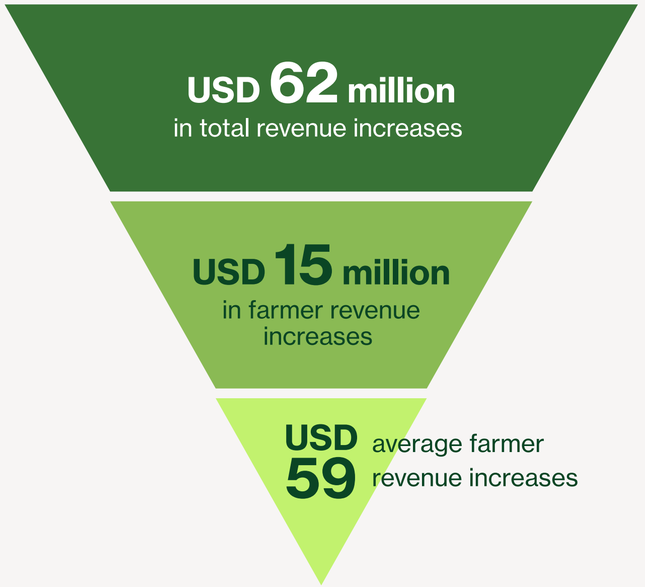
Economic Implications of Crop Protection AI Early Adopters (Scenario 1)

Anticipating the impact at the farmer level, over 250,300 Rwandan farmers, or 10% of SHFs engaged in cultivating the top five crops, are deemed well-positioned to adopt this AI technology. This is considering the current state of digital literacy among rural dwellers. AI adoption is expected to yield USD 14.9 million in additional revenue for these farmers, translating to an average of USD 59 in extra revenue per farmer per planting cycle. Though this sum seems insignificant, it can make a world of difference to rural families; this additional revenue covers the annual expenses of elementary and secondary school for day students who attend government schools.[115]

The benefits of AI adoption do not stop at the farmer level. The 250,300 early adopters of AI would be responsible for fostering a total of USD 61.9 million for the entire economy, USD 14.9 million of which would

Gross yield improvement
resulting from AI use

Yield improvement and economic implications of crop AI adoption
by early adopters (Scenario 1)



benefit SHFs directly, with the rest divided amongst actors in other areas of the agricultural economy, such as distributors, storage providers, and sellers.

Additionally, AI uptake in food production can make a big impact on regional food insecurity. Adopting AI to diagnose crop deficiencies can lead to salvaging an additional 31,200 tons of bananas, 19,400 tons of sweet potatoes, 19,200 tons of cassava, and so on, as seen in the previous visual (page 58).

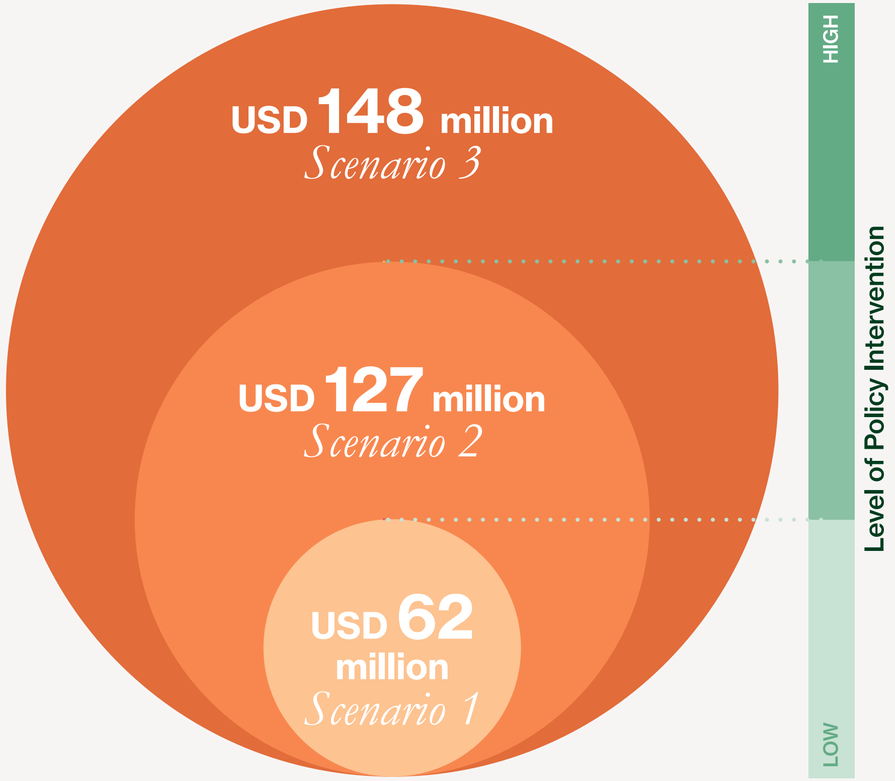
Economic Implications of Policy Interventions Buoying AI Adoption (Scenario Analyses)

There is even more potential value to capture through reaching more farmers beyond the early adopters, if the following six policy recommendations are implemented:

- Increase Rural Electrification
- Improve Internet Access
- Expand Access to Smartphones
- Enhance Functional Literacy
- Foster Trust in Technology in Rural Communities
- Develop a Vibrant AI Culture

Economic implication of crop AI adoption

Under three adoption scenarios



The early adoption of AI holds the potential for a collective increase in farmer revenue by USD 14.9 million across all five crops. However, the potential for revenue improvement could more than double if a greater number of farmers can adopt AI technology thanks to the implementation of the policies recommended in this report. If adoption increases from 10% (scenario 1) to 21% (scenario 2), revenue gains would rise to a total of USD 126.7 million, USD 30.4 million of which would benefit SHFs directy.

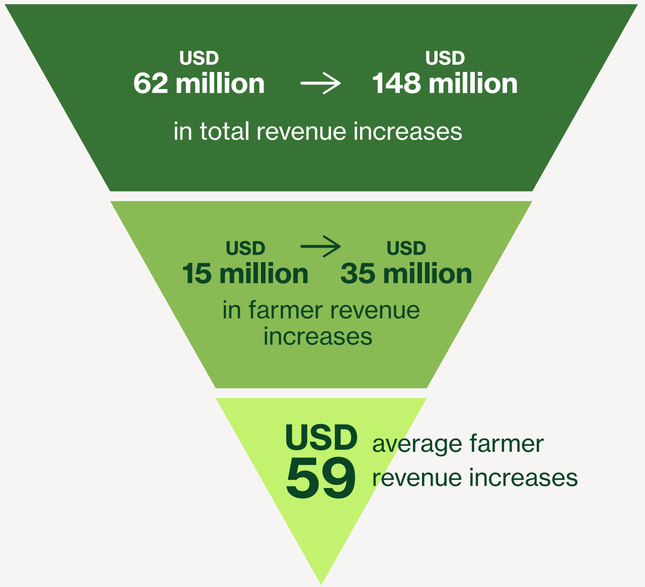
These revenue gains would be even higher if policymakers pursue rigorous policy interventions. Raising the probability of adoption to 24% through enacting the previous policy recommendations in a rigorous, holistic, and sustainable fashion would lead to an economy-wide revenue increase of USD 147.5 million, which would benefit 595,900 SHFs and countless other actors in the regional food supply chain.

Economic Impact of Crop AI Adoption Across the Three Scenarios

Approximately 0.47% to 1.11% GDP increase. Deploying Crop AI across the top five cultivated crops is projected to contribute approximately 0.47% to 1.11% to Rwanda's GDP, resulting in an additional revenue range of USD 61.9 million to USD 147.5 million, as previously discussed. This newfound revenue, distributed across the food production and distribution value chain, is estimated to directly impact many households.

Approximately 1.89% to 4.46% boost to the agricultural sector. Furthermore, introducing Crop AI across the top five crops could lead to a substantial 1.89% to 4.46% increase in the contribution of agriculture, fishery, and forestry to the overall economy. At the current rate of adoption, roughly 250,300 SHFs cultivating the top five crops would benefit. The 4.46% increase, however, can only be achieved if AI uptake increases to 24% through rigorous policy intervention, which would increase the impact from 250,300 SHFs to 595,900 SHFs growing the top five crops.

Potential value creation
from policy interventions

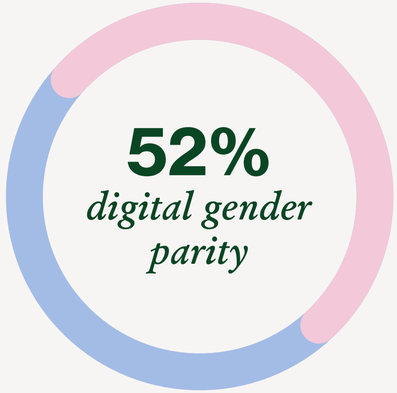


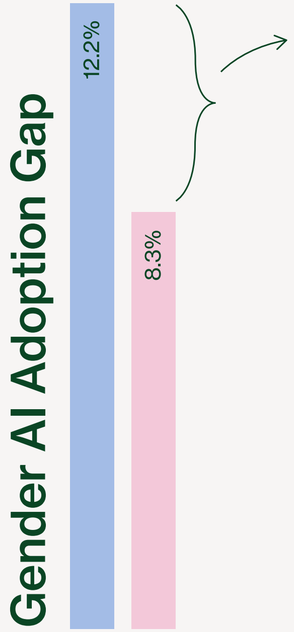
Bridging the Gender Gap

Our estimation reveals a 4-percentage point gender gap in AI adoption between women and men Rwandan farmers. To approximate this number, we built upon our *Progress to Digital Parity Study*, which benchmarks Rwanda's progress in bridging the digital gender divide and achieving an inclusive digital economy for all. The methodology for this analysis can be found in Appendix 3.3.

Despite women constituting 56% of farmers,[116] our projections suggest that only 114,700 out of the estimated 1.4 million women growing the top five crops are likely to be early adopters. Addressing this gender digital gap has the potential to instigate a significant advancement in Crop AI adoption.

Bridging the gender adoption gap could positively impact an additional 54,600 women SHFs actively engaged in the cultivation of the top five crops. This collective effort has the potential to generate USD 3.2 million in additional revenue exclusively for these women, marking a substantial stride towards gender-inclusive technological adoption in Rwandan agriculture.





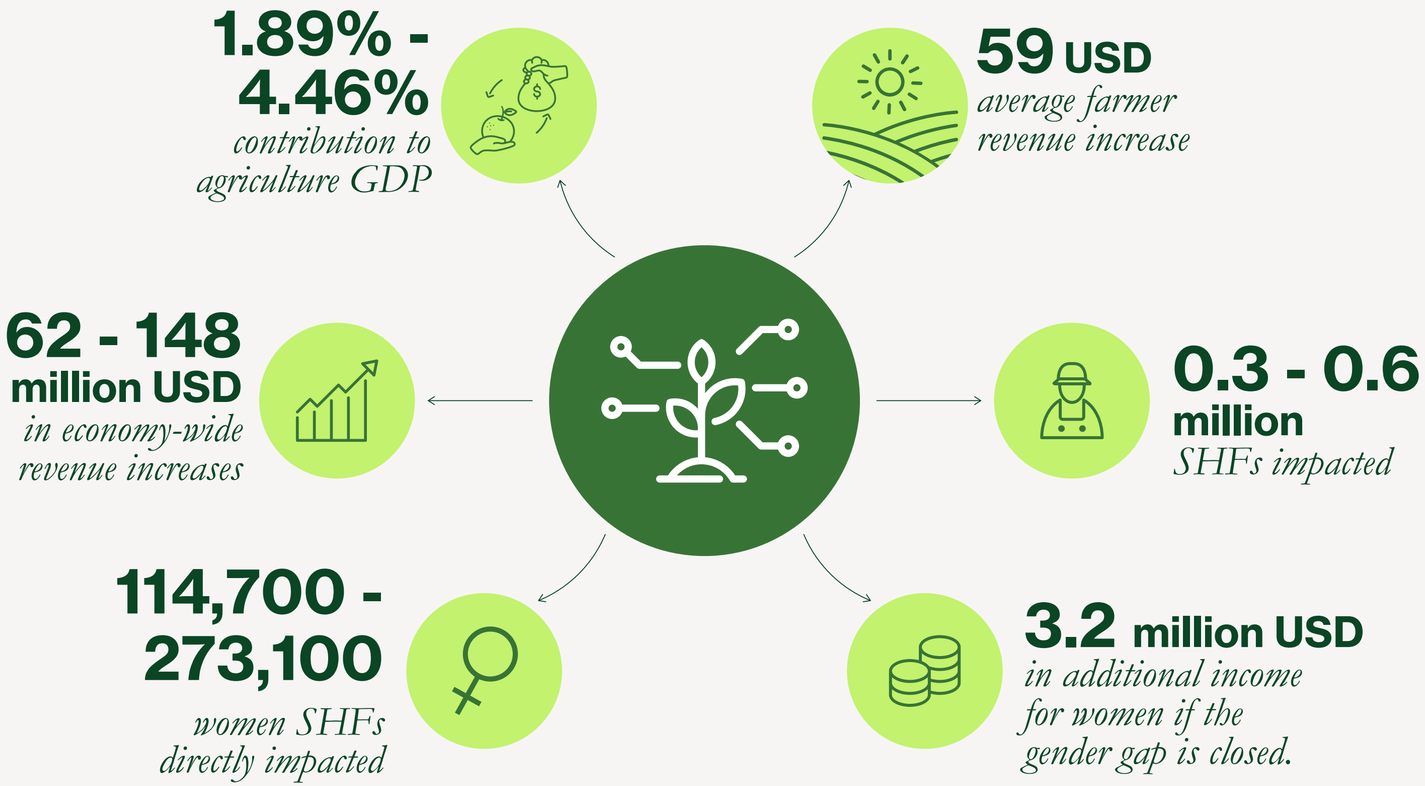
3.9%
gender adoption gap in AI

54,600
additional women smallholder farmers

USD 3.2 million
in additional income generated

Despite women constituting 55.5% of farmers, our projections suggest that only 114,700 out of the estimated 1.4 million female farmers 8.3% are likely to be early adopters.

Economic Impact Summary



Country Insights and Scenario Analyses

Tanzania

24%

agricultural contribution to Tanzania's GDP[117]

64%

of Tanzania's labor force works in the agriculture sector[118]

3.4 million

Tanzanian smallholder farmers growing the top five crops

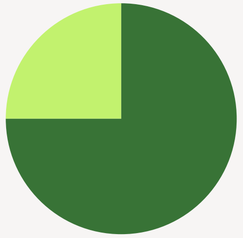
Tanzania

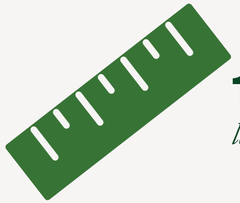
Country Summary

- Agriculture constitutes one-fourth of the economy[119] and employs two-thirds of the labor force,[120] with SHFs contributing significantly to food production.
- Traditional farming practices are common in Tanzania, and only 1.4% of SHFs use motorized equipment, 16% use fertilizers, and 42% have access to improved seeds.[121]
- The World Bank recognizes the agriculture sector's growth potential to alleviate poverty in a country where 4 in 10 people live in poverty[122] as of 2023.[123]
- In Tanzania, 1 in 3 people is undernourished.[124] Studies have shown that, with every flood or drought, there is a 5% to 20% increase in food insecurity.[125]
- Tanzania ranks 90th out of 113 countries on the Global Food Security Index.[126]

8/10 *farmers in Tanzania are smallholders*[127]

75% *of food produced in Tanzania is by smallholder farmers*[128]





1.2 ha *is the mean landholding capacity of SHFs*[129]

137th */193 in the AI Government Readiness Index*[130]

RANK

136*th*
137*th*
138*th*

AI Landscape

Tanzania is yet to form a cohesive government approach to AI adoption. Although start-ups operate with little regulation and often lack funding for new ventures,[131] AI technologies have been slowly penetrating the market. They have primarily been utilized in AI Chatbots[132] and the health sector, specifically in improving efficiency in delivery and supply chain management and providing advice on a range of medical topics.[133] This concentration in the health sector has provoked a positive response at the government level; in 2023, the Ministry of Health was in the process of drafting an AI Policy Framework to guide government stances on emerging AI tech.[134]

Tanzania's AI innovation space holds a lot of potential. The University of Dodoma (UDOM) and the Nelson Mandela African Institute of Science and Technology (NM-AIST) are leading the charge in the region's multidisciplinary AI research, exemplified by the establishment of the Artificial Intelligence for Development of Africa's Anglophone research lab.[135]

While AI adoption in Tanzania is still in its early stages, it holds the potential for significant long-term growth in crucial sectors, including agriculture. Nuru AI[136] and Agrobot,[137] both of which offer agronomic consulting through smartphone apps or SMS, are just two examples of the type of innovation that promises meaningful impact in the Tanzanian agricultural space.

Economic Impact of Crop Protection AI Adoption

Economic Implications of Crop Protection AI Early Adopters (Scenario 1)

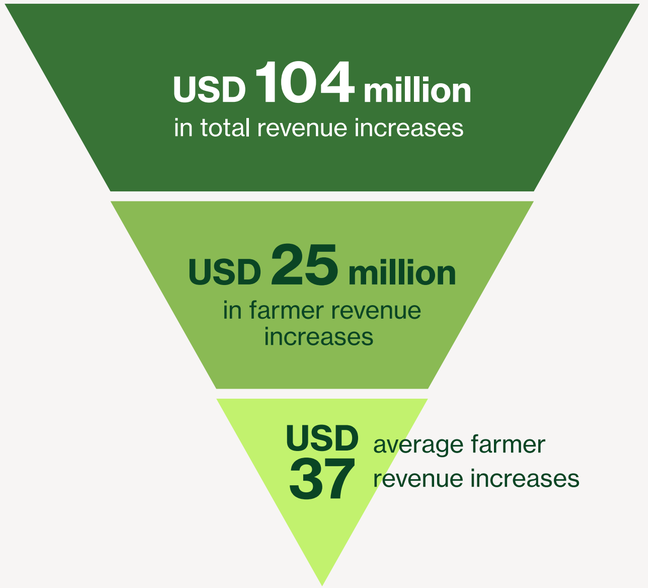
Judging by Tanzania's current smartphone penetration and level of digital literacy, we expect 20% of SHFs growing the top five crops to be early adopters of Crop AI. This amounts to 690,100 SHFs, demonstrating how ripe Tanzania's agricultural sector is for technological transformation.

AI uptake is projected to generate USD 25 million in additional revenue for these early adopting farmers, equating to an average of USD 37 in extra revenue per farmer per planting cycle. While this average revenue increase may seem insignificant at face value, a farmer producing one of the top five crops can send an additional child to school for half a year from the additional income generated from one planting cycle.[138]

The economic benefits do not stop at the farmer level. The ripple effects of this newfound productivity generated by AI uptake would increase country-

Gross yield improvement
resulting from AI use

Yield improvement and economic implications of crop AI adoption
by early adopters (Scenario 1)



wide revenue by a total of USD 104.1 million. Of this sum, USD 25 million benefits SHFs directly and USD 67.1 million is distributed throughout the food production and distribution value chain, directly influencing thousands of households.

Additionally, the adoption of this technology by these early adopters has the potential to enhance food security in the country. For example, maize supply could experience a significant increase of 139,200 tons per planting cycle, cassava a 121,100 ton increase, and so forth, as explained in the previous visual.

Economic Implications of Policy Interventions Buoying AI Adoption (Scenario Analyses)

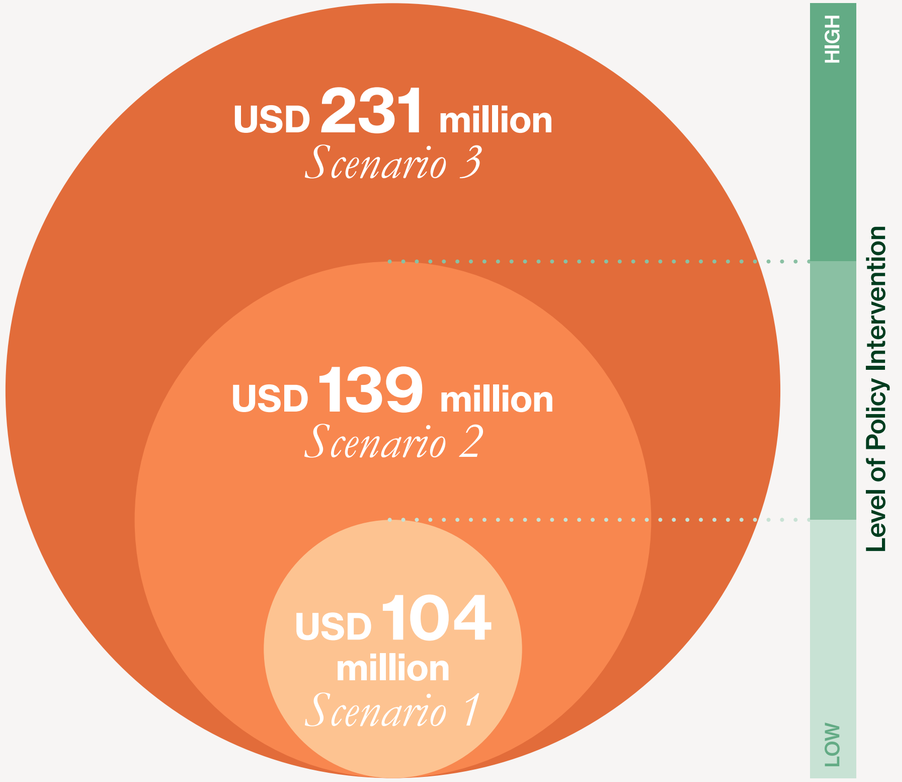
The following six policy recommendations, if implemented, could expand the impact of AI technology beyond early adoption:

- Increase Rural Electrification
- Improve Internet Access
- Expand Access to Smartphones
- Enhance Functional Literacy
- Foster Trust in Technology in Rural Communities
- Develop a Vibrant AI Culture

Farmers' revenue stands to more than double if AI adoption increases, a goal achievable through the implementation of the six proposed policy recommendations. The collective impact has the potential to transform the Tanzanian agricultural economy.

Economic implication of crop AI adoption

Under three adoption scenarios



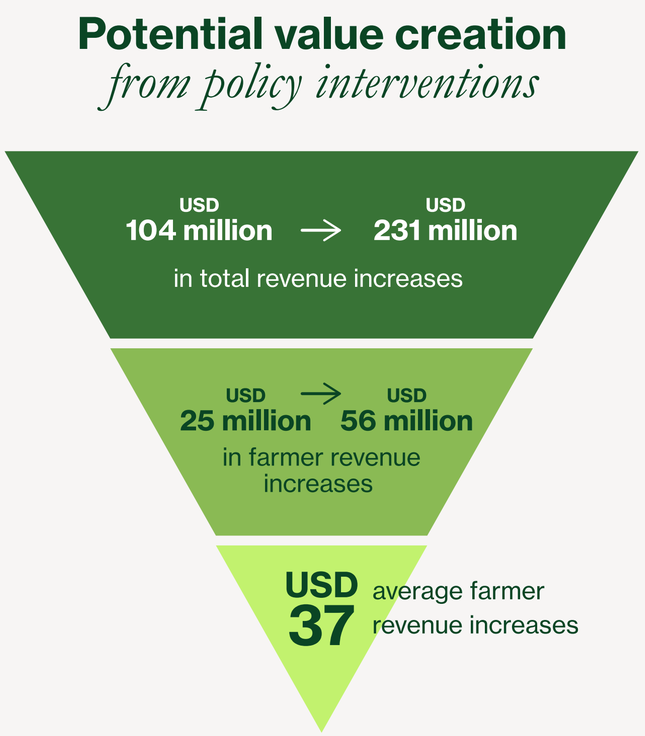
In the absence of policy change (scenario 1), as discussed in the previous section, the initial adoption of AI holds the potential for a USD 104.1 million increase in revenue within the Tanzanian economy. If policymakers enact the AI-enabling policy interventions recommended in this report, then we predict AI adoption can be as high as 45% instead of its current 20%. The outlook for revenue improvement would therefore see a substantial increase, from USD 104.1 million to USD 231.4 million, due to a wider base of SHFs adopting the technology. Of these USD 231.4 million, roughly USD 55.5 million would directly benefit 1.5 million SHFs growing the top five crops; the rest would be spread across the agricultural value chain.

The previous visual (page 68) demonstrates how increasing adoption through targeted policy intervention can more than double economy-wide revenue improvements.

Economic Impact of Crop AI Adoption Across the Three Scenarios

Approximately 0.14% to 0.31% GDP increase. The introduction of Crop AI across the top five cultivated crops in Tanzania holds significant promise for economic growth and agricultural development. This implementation has the potential to contribute approximately 0.14% to 0.31% to the GDP, resulting in an additional revenue ranging between USD 104.1 million to USD 231.4 million. The envisioned revenue boost, distributed across the food production and distribution value chain, is expected to directly impact many households.

Approximately 0.58% to 1.28% boost to the agricultural sector. Moreover, this technological advancement could lead to a substantial 0.58% to 1.28% increase in the contribution of the agriculture, fishery, and forestry sector to the economy. The implications of such a boost extend beyond individual farmers, influencing the broader economic landscape. At the current scale, 690,100 farmers will benefit from this Crop AI technology. However, with the suggested policy implementation, up to 1.5 million farmers will benefit from this Crop AI technology; this is approximately half of the SHFs growing the top five crops.

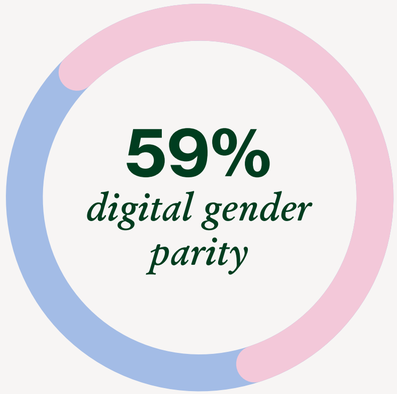


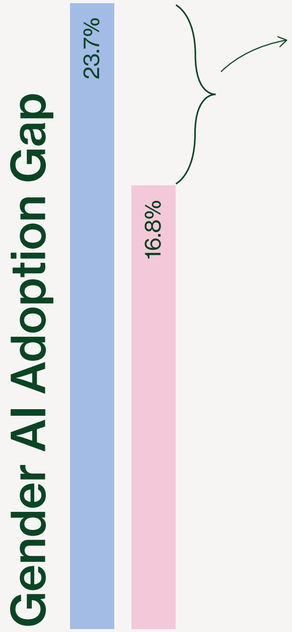
Bridging the Gender Gap

Our estimation indicates a 7-percentage point gender gap in AI adoption between men and women SHFs in Tanzania. To approximate this number, we built upon our *Progress to Digital Parity Study*, which benchmarks Tanzania's progress in bridging the digital gender divide. The methodology for this analysis can be found in Appendix 3.3.

Despite women constituting 50% of farmers,[139] our projections suggest that only 286,500 out of the estimated 1.7 million women farmers (17%) growing the top five crops are likely to be early adopters. Addressing this gender digital gap holds the potential to usher in a significant advancement in Crop AI adoption.

Bridging the 7% gender gap in AI adoption could have a positive impact on an additional 119,000 women smallholder farmers actively involved in the cultivation of the top five crops. This collective endeavor has the potential to generate USD 4.4 million in additional revenue exclusively for these women SHFs, marking a substantial stride toward gender-inclusive technological adoption in agriculture.





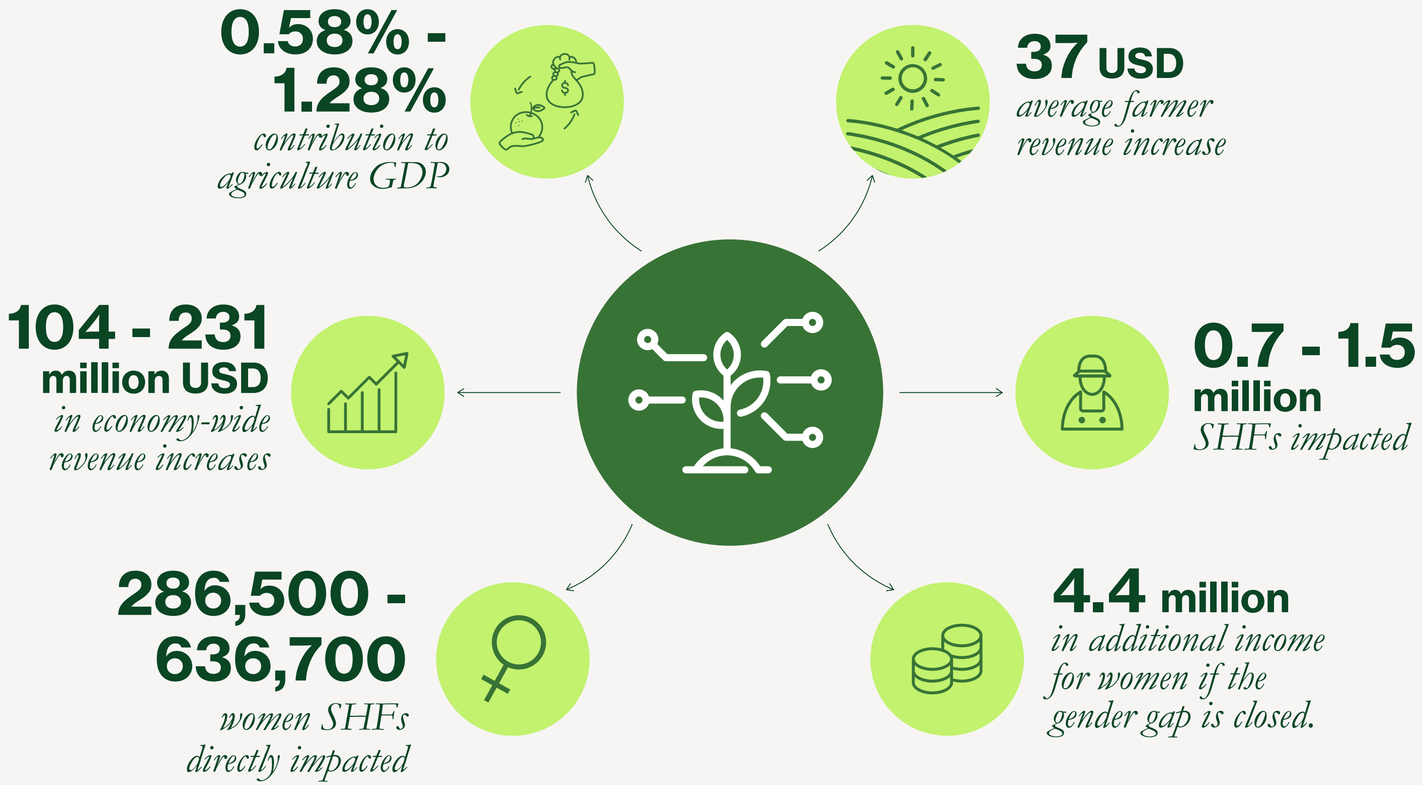
7%
gender adoption gap in AI

119,000
additional women smallholder farmers

USD 4.4 million
in additional income generated

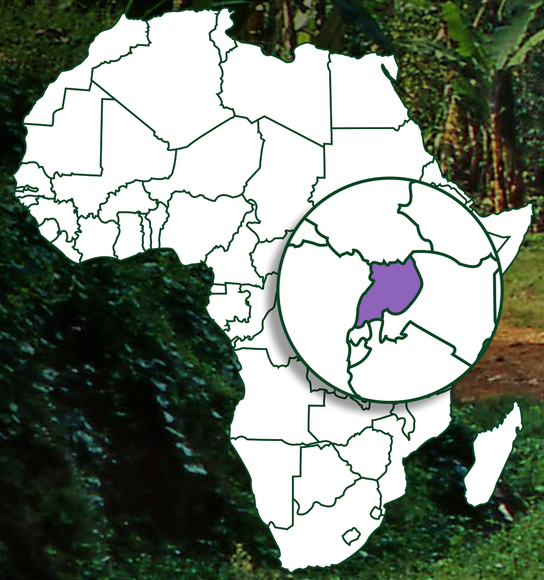
Despite women constituting 50% of farmers, our projections suggest that only 287,000 out of the estimated 1.7 million female farmers (17%) are likely to be early adopters.

Economic Impact Summary



Country Insights and Scenario Analyses

Uganda



24%

agricultural contribution to Uganda's GDP[140]

63%

of Uganda's labor force works in the agriculture sector[141]

3 million

Ugandan smallholder farmers growing the top five crops

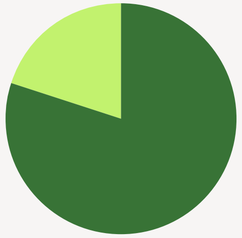
Uganda

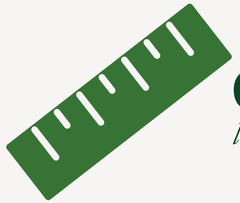
Country Summary

- The agricultural sector is a significant contributor to the country's economy, employing 80% of the labor force and providing 85% of its exports.[142]
- Uganda's fertile agricultural land holds the capacity to sustainably feed up to 200 million people. Despite 80% of Uganda's land being suitable for agriculture, only 35% is currently under cultivation.[143]
- While over 80% of the crops are food crops, a limited number of households have access to improved seeds (19%) and only 4.4% use fertilizers. Moreover, just 0.7% of the average household's farmland is irrigated, and only 0.7% of smallholders have motorized equipment.[144]
- 34% of the population lives below USD 1.90 a day, with the majority residing in rural areas (84%). Furthermore, 27% of SHFs live below the poverty line.[145]
- Uganda ranks 93rd out of 113 countries in the Global Food Security Index.[146]

9/10 *farmers in Uganda are smallholders*[147]

80% *of the agricultural production is by SHFs*[148]





0.97 ha *is the mean landholding capacity of SHFs*[149]

132nd */ 193 in the AI Government Readiness Index*[150]

RANK

131st
132nd
133rd

AI Landscape

AI in Uganda has made inroads in technological development and has been adopted through various ongoing projects. In 2019, Uganda formed a national expertise task force to steer government efforts to incorporate tech into economic development projects.[151] While the country is still in the nascent stages of deploying AI-enabled technologies, its use is nevertheless observed in certain businesses to respond to customer queries, advertising, supply chain management, etc.[152] The UN has identified 21 companies, 20 start-ups, 12 Hub & Business Developments and more in its mapping of AI initiatives in Uganda.[153]

Prominent technology-related initiatives have also been introduced in the agricultural sector. The UNFCC, for example, provides farmers with agricultural advisory services by employing ICT, which has led to a 65% decrease in crop loss.[154] Furthermore, NASA Harvest has implemented AI projects to support farmers and enhance agricultural production.[155] These initiatives utilize images and ground data such as location and crop information to accurately evaluate food insecurity and climate change, providing valuable insights for agricultural improvement. Research projects in agriculture related to crop yield, agriculture advisory for SHFs, prediction analysis, and more have been undertaken by the Makerere AI Lab at the Makerere University in Kampala.[156] These initiatives demonstrate Uganda is ripe for AI adoption.

Economic Impact of Crop Protection AI Adoption

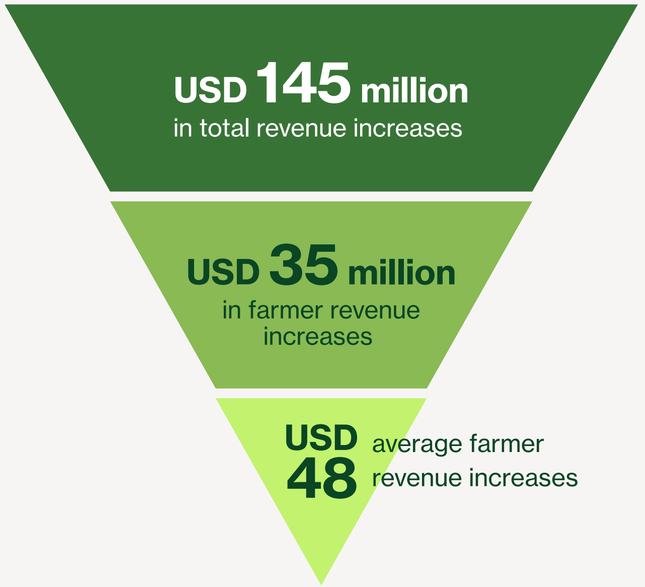
Economic Implications of Crop Protection AI Early Adopters (Scenario 1)

We predict a substantial number of Ugandan farmers are well-positioned to embrace AI technology. Considering the existing state of digital literacy among rural dwellers, we expect roughly 730,700 SHFs growing the top five crops will be early adopters of AI for agriculture. This adoption is poised to generate USD 34.7 million in additional revenue for these farmers, equating to an average of USD 48 in extra revenue per farmer per planting cycle. Notably, the surplus revenue from a single planting cycle is nearly sufficient to cover one-term school charges in a government school for a child.[157]

Adoption of AI by the previously mentioned “early adopters” (which amount to 730,700 SHFs) would have economic ripple effects throughout the entire Ugandan economy. Adoption of Crop AI would lead to an additional USD 110 million in revenue increases for other actors all along the agricultural value chain, ranging from

Gross yield improvement
resulting from AI use

Yield improvement and economic implications of crop AI adoption
by early adopters (Scenario 1)



transporters to storers to sellers and more. When added up, the total revenue increases between farmers and other actors tallies up to USD 144.8 million. This surge in revenue will bring about significant improvements in the lives of all Ugandans, enhancing their access to resources and addressing other challenges related to poverty and food insecurity in the country.

Additionally, the use of Crop AI would contribute immensely to regional food security. Yields are expected to rise due to a substantial reduction in crop loss, leading to thousands of tons in additional produce in the market. For the top five crops, plantains and cooking bananas would increase by 238,700 tons, maize by 72,600 tons, cassava by 69,500 tons, beans by 22,200 tons, and coffee by 9,700 tons, as illustrated in the adjacent visual. This increase in farmer revenue will contribute to an overall economy-wide upswing in GDP by USD 144.8 million.

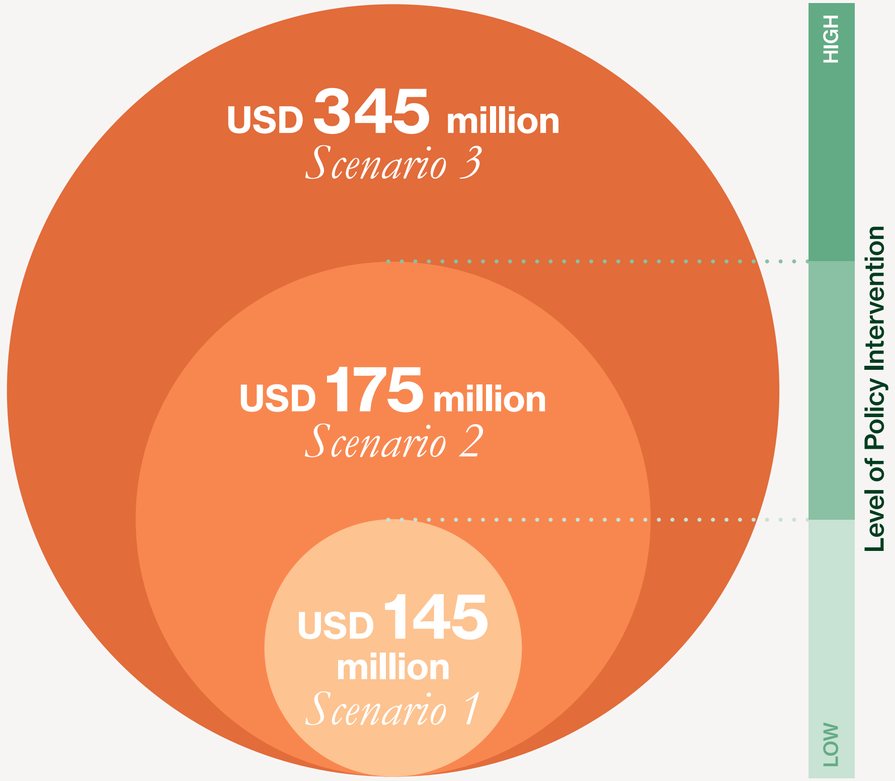
Economic Implications of Policy Interventions Buoying AI Adoption (Scenario Analyses)

The following six policy recommendations, if implemented, could expand the impact of AI technology beyond early adoption:

- Increase Rural Electrification
- Improve Internet Access
- Expand Access to Smartphones
- Enhance Functional Literacy
- Foster Trust in Technology in Rural Communities
- Develop a Vibrant AI Culture

Economic implication of crop AI adoption

Under three adoption scenarios



These recommendations are crucial to enable farmers to access and integrate AI into their farming practices on a larger scale. If some of these policy areas are implemented, we expect adoption rates to increase from 24% (as envisaged in scenario 1) to 29% (as envisaged in scenario 2). This heightened adoption is expected to amplify total economy-wide revenue gains from USD 144.8 million (scenario 1) to USD 174.7 million (scenario 2).

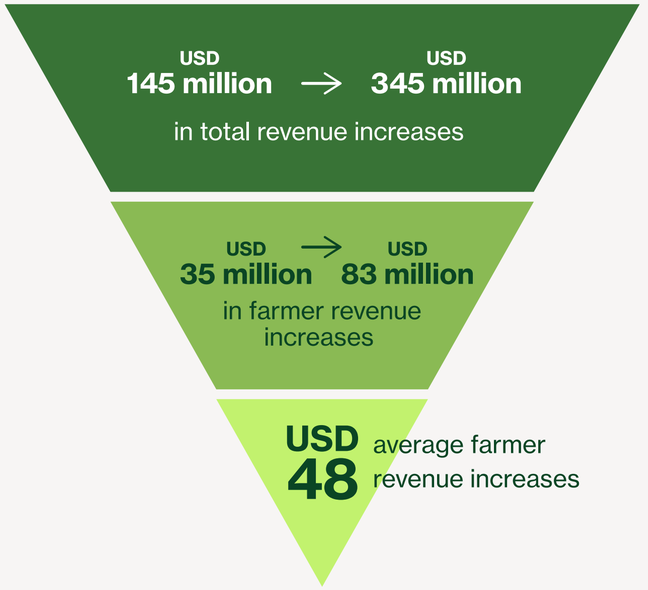
If policymakers pursue stringent implementation of policy, we expect adoption to be as high as 58% (which we call scenario 3: holistic policy intervention). With advancements made through rigorous policy intervention, the projected revenue growth is estimated to soar from USD 174.7 million to USD 344.6 million, signifying a profound impact on the entire Ugandan economy. Of these USD 344.6 million, USD 82.7 million would benefit SHFs directly, and the rest would be divided among other actors in the agricultural economy. Thus, this substantial increase would have a major impact on the livelihoods of countless households in Uganda's agricultural economy.

Economic Impact of Crop AI Adoption Across the Three Scenarios

Approximately 0.32% to 0.76% GDP increase. Deploying Crop AI across the top five cultivated crops is projected to contribute approximately 0.32% to 0.76% to the GDP, resulting in an additional revenue range of USD 144.8 million to USD 344.6 million. This newfound revenue, distributed across the food production and distribution value chain, is estimated to directly impact thousands of households.

Approximately 1.33% to 3.15% boost to the agricultural sector. Introducing Crop AI across the top five crops could lead to a substantial 1.33% to 3.15% increase in the contribution of agriculture, fishery, and forestry to the overall economy. This demonstrates that the potential for revenue improvement could more than double if a greater number of farmers can adopt AI technology through the implementation of policies recommended in this report.

Potential value creation
from policy interventions

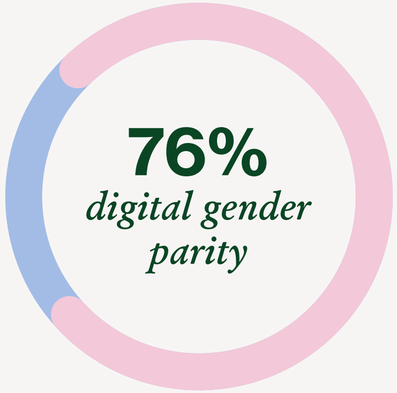


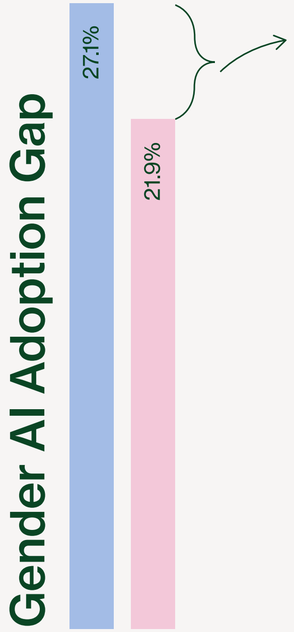
Bridging the Gender Gap

Our estimation reveals a 5-percentage point gender gap in AI adoption between women and men Ugandan farmers. To approximate this number, we built upon our *Progress to Digital Parity Study*, which benchmarks Uganda's progress in bridging the digital gender divide and achieving an inclusive digital economy for all. The methodology for this analysis can be found in Appendix 3.3.

Despite women constituting 53% of farmers,[158] our projections suggest that only 346,300 out of the estimated 1.6 million women farmers growing the top five crops are likely to be early adopters. Addressing this gender digital gap holds the potential to instigate a significant advancement in Crop AI adoption.

Bridging the gender adoption gap could positively impact an additional 82,200 women smallholder farmers actively engaged in the cultivation of the top five crops. This collective effort has the potential to generate USD 3.9 million in additional revenue exclusively for these women, marking a substantial stride towards gender-inclusive technological adoption in Ugandan agriculture.





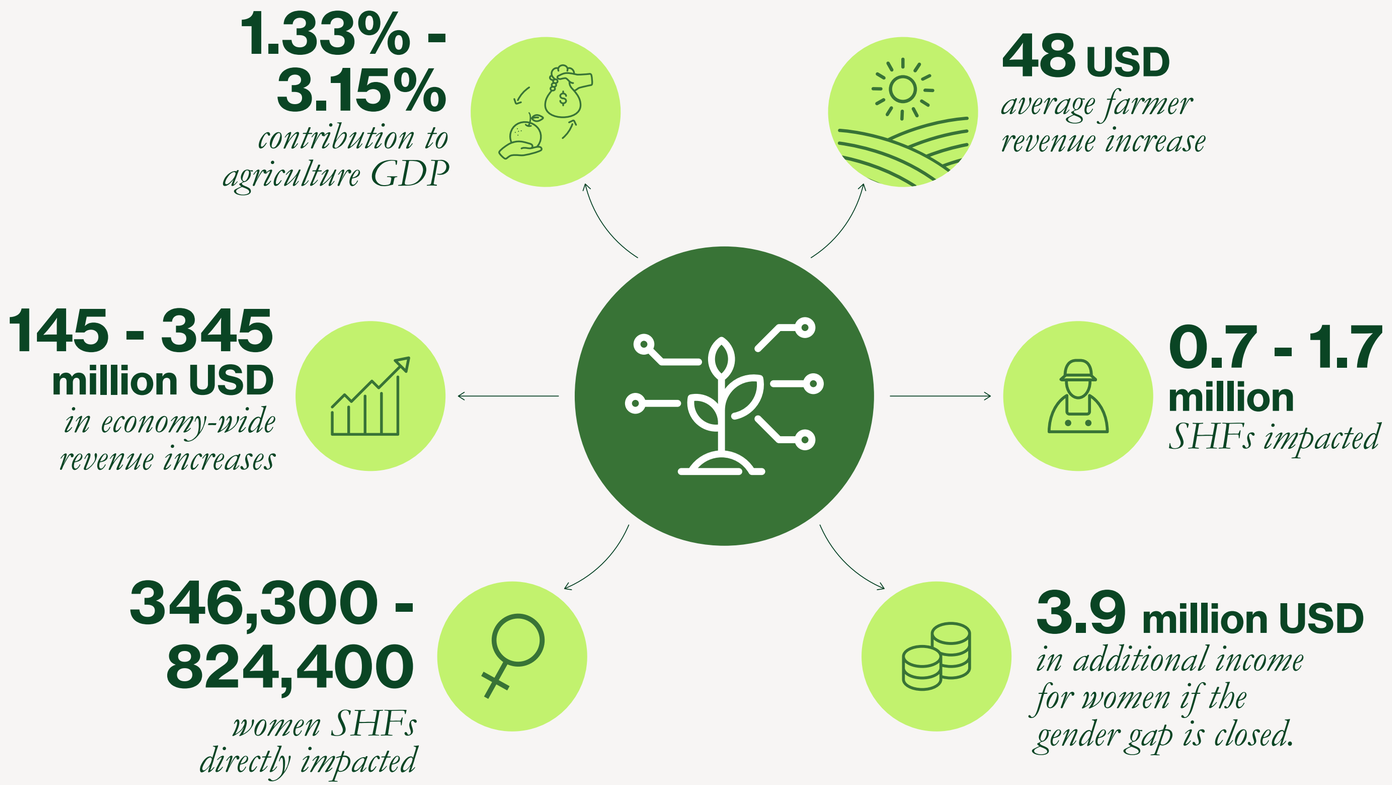
5.2%
gender adoption gap in AI

82,200
additional women smallholder farmers

USD 3.9 million
in additional income generated

Despite women constituting 52.7% of farmers, our projections suggest that only 346,300 out of the estimated 1.6 million female farmers 21.9% are likely to be early adopters.

Economic Impact Summary



Implications for Action: Country Policy Recommendation Matrix

To understand how economies can achieve these economic and social gains, we identified six central policy recommendations aimed at increasing AI uptake in the agricultural sphere. We highlight actions that address both infrastructure and capacity challenges.

The infrastructure enablers, which are the first three in the table below, focus on expanding the accessibility of infrastructure and technology. The capacity enablers focus on enhancing a country's AI development capacity, digital literacy, and digital trust, therefore tackling both supply and demand components of the AI economy.

For our analysis, we used South Africa's progress in each of these policy areas as a benchmark to understand the relative state of each country's progress in the region. South Africa's performance in each of these categories is a good comparison given that, unlike countries outside the region, it shares some of the biggest contemporary challenges faced by the seven countries in question. Additionally, it is a global leader in using technology to craft innovative and disruptive agritech solutions to current farming challenges, further indicating that it can be used as a role model for countries in the region who are interested in pursuing tech solutions.[159]

The pink cells mean that the given county is behind relative to the region's leader, while the green cells indicate that they meet the benchmark in that specific policy area. For more information on proxies and calculation methods, refer to Appendix 4.1.

Normalizing the values of each of these recommendations allows us to create a hierarchized list of priorities catered to each country's reality. Doing so gives us an understanding of which challenges are country-specific and which ones are common across the region.

AI culture development, for example, is the policy area that is least developed across all seven countries. Presence of companies that specialize in AI, which we measure per million people, is indicative of whether the AI adoption is reflective of the country's contemporary realities. Locally developed AI applications increase trust in technological solutions and are more in line with local demands and needs. South Africa boasts a rate of 12.12, while Kenya, the closest of the seven countries studied, makes up only a third of that. All other countries have less than a fifth of South Africa's rate, with the lowest being Ethiopia at roughly 1% of South Africa's AI company presence.

Additionally, trust in technology, as measured by the use of digital payments, presents the most amount of variegation amongst all countries. Kenya and Uganda are the farthest ahead, with Kenya being merely three points behind South Africa. Ethiopia, Nigeria, and Rwanda have the most room for improvement, while Côte d'Ivoire and Tanzania are on track but still over 30 points behind South Africa. Trust in technology is therefore an urgent priority across most countries. Lack of trust in these solutions is a central barrier for AI adoption and, consequently, an issue that curtails the revenue gains technology can bring.

Furthermore, rural electrification ranks as the most urgent infrastructure enabler for all countries except Kenya, indicating that access to power is still a significant barrier to AI adoption in rural communities. Internet access is the next most pressing infrastructure-related policy area. All seven countries studied have under 40% rural internet access (over 20 percentage points behind South Africa), indicating that a revitalized effort to connect rural SHFs to the internet is crucial to AI uptake.

Lastly, smartphone accessibility should not be overlooked. Though the statistics in the previous table show national smartphone access, they give us an understanding of the state of rural smartphone adoption, further cementing it as an area ripe for policy intervention. Smartphones are indispensable for Crop AI, and not allocating an adequate amount of attention to this policy priority can lead to slower uptake and, consequently, decreased revenue gains. The gender gap in smartphone adoption should also be addressed. For instance, there is a 36% gap between men's and women's mobile phone access in Ethiopia.[160]

Viewing AI uptake as the result of AI and AI-adjacent enablers allows policymakers to understand the importance of holistic approaches to technological adoption. These guidelines offer a quantitative understanding of where priorities should lie and, consequently, how policymakers should apportion limited resources.

Viewing AI uptake as the result of AI and AI-adjacent enablers allows policymakers to understand the importance of holistic approaches to technological adoption.

Policy Matrix

Country	Infrastructure Enablers			Capacity Enablers		
	Increase Rural Electrification (rural access to electricity)	Improve Internet Access (rural population using the internet)	Expand access to smartphone (percentage of smartphones connections)	Enhance Functional Literacy (literacy rate)	Foster Trust in Technology in Rural Communities (made or received a digital payment, rural)	Develop a Vibrant AI Culture (companies that specialize in AI per million people)
Côte d'Ivoire	43%	39%	56%	90%	43%	1.03
Ethiopia	39%	29%	43%	52%	13%	0.15
Kenya	63%	35%	46%	83%	74%	3.78
Nigeria	25%	31%	44%	78%	24%	2.09
Rwanda	38%	30%	42%	76%	24%	1.52
Tanzania	22%	25%	45%	82%	45%	0.67
Uganda	33%	25%	42%	79%	58%	0.93
South Africa	93%	61%	67%	90%	77%	12.12

Sources: Rural Access to Electricity (World Bank); Rural Population Using the Internet (Euromonitor and Digital Planet); Percentage of Smartphone Connections (GSMA); Literacy Rate (World Bank); Made or Received a Digital Payment, Rural (Findex); Companies That Specialize in AI per million people (State of AI in Africa Report)

Categories Lacking | Needs Improvement | On Track | Advancing | Meets Benchmark

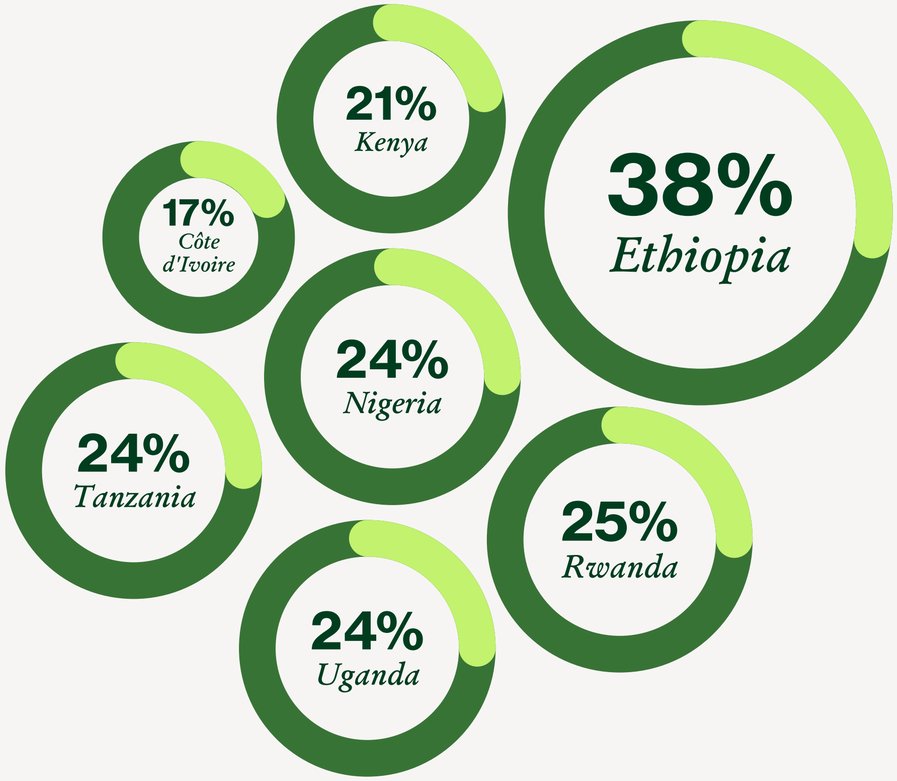
Appendix

1.1 Country Selection

The countries featured in this report were selected through a meticulous process based on criteria such as their performance on Digital Planet's *Digital Intelligence Index (DII)*, data availability, and the respective contribution of their agriculture sector to the national GDP.[161]

Initially, the DII served as a foundation for identifying Sub-Saharan African countries well-positioned to harness the advantages of AI. Subsequently, we refined the selection by focusing on countries where the agricultural sector contributes at least 20% to the GDP, resulting in the inclusion of six countries under study.

Côte d'Ivoire, the seventh country, was added due to the potential for outsized benefits from AI adoption, primarily attributed to its particularly substantial cocoa sector.[162] This meticulous selection process ensures a comprehensive and strategic analysis of countries poised to make significant strides in AI adoption within the context of their agricultural landscape.



1.2 Crop Selection

Once we finalized the country list, we proceeded to identify the top five crops in each country to see where AI adoption practices could yield the biggest impact (table below). We looked at each crop's gross production value, economic importance, and data availability.[163] This yielded the following list of crops for each country.

Côte d'Ivoire

Crop	GPV (million USD)	Percent Contribution
Cocoa	2,760.9	22.10%
Cassava	1,714.0	13.70%
Rice	1,614.8	12.90%
Yams	1,036.3	8.30%
Bananas	847.2	6.80%
Total for Top 5 crops	**7,973.2**	**63.90%**

Ethiopia

Crop	GPV (million USD)	Percent Contribution
Maize	1,811.7	9.50%
Wheat	1,614.8	8.40%
Sorghum	1,387.2	7.30%
Barley	610.6	3.20%
Coffee	461.9	2.40%
Total for Top 5 crops	**5,886.2**	**30.80%**

Nigeria

Crop	GPV (million USD)	Percent Contribution
Yams	19,330.6	40.3%
Cassava	5,382	11.2%
Maize	4,649.4	9.7%
Sorghum	2,146.5	4.5%
Tomatoes	1,417.4	3.0%
Total for Top 5 crops	**32,935.9**	**68.7%**

Tanzania

Crop	GPV (million USD)	Percent Contribution
Maize	1,875.5	19.50%
Bananas	1,458.6	15.10%
Cassava	1,214.0	12.60%
Rice	1,089.7	11.30%
Beans	777.6	8.10%
Total for Top 5 crops	**6,415.4**	**66.60%**

Kenya

Crop	GPV (million USD)	Percent Contribution
Tea Leaves	2,770.7	25.80%
Maize	1,052.2	12.20%
Potatoes	539.9	6.35%
Beans	522.7	6.10%
Bananas	427.9	5.00%
Total for Top 5 crops	**5,313.4**	**55.30%**

Rwanda

Crop	GPV (million USD)	Percent Contribution
Bananas	742.8	22.10%
Cassava	297.7	8.9%
Beans	253.8	7.5%
Potatoes	247.9	7.4%
Sweat Potatoes	238.9	7.1%
Total for Top 5 crops	**1,781.1**	**53.0%**

Uganda

Crop	GPV (million USD)	Percent Contribution
Bananas (P&C)	2,050.8	23.00%
Cassava	611.3	6.90%
Beans	609.5	6.80%
Maize	605.3	6.80%
Coffee	598.7	6.70%
Total for Top 5 crops	**4,475.6**	**50.20%**

1.3 Estimating the Addressable Market

Our report zeroes in on smallholder farmers due to their significant potential benefits from AI solutions. These farmers play a crucial role in food production, accounting for the majority of consumed food in these countries, encompassing over half of the population yet often find themselves overlooked by the market.

Characteristically, a smallholder farmer (SHFs) operates small-scale farms primarily dedicated to food crop production, with a modest surplus often available for sale. Definitions of small-scale farms vary across countries; for example, Rwanda's average SHFs operates on less than 0.5 hectares, while Tanzania's is 1.2 hectares.[164] Acknowledging this diversity, our analysis considers local definitions of SHFs from various sources.

To comprehend the smallholder landscape, we calculated the number of SHFs cultivating the top five crops in the seven selected countries. This involved determining what portion of all land allocated (LandAll)[165] to agriculture belonged to smallholder farmers (LASHF%), which was derived by using the average farm size of farmers with small farms (avgSFarm) and big farms (avgBFarm)[166,167,168] and combining them with the percentage of small farms (%SFarm)[169,170,171] and big farms (%BFarm). The formula is therefore the following:

$$\text{LASHF\%} = \frac{\text{\%SFarm} * \text{avgSFarm}}{(\text{\%SFarm} * \text{avgSFarm}) + (\text{\%BFarm} * \text{avgBFarm})}$$

Once we defined the percentage of land belonging to smallholder farmers, we proceeded to estimate the total number of SHFs (SHFEst) in the country by dividing the total land allocated to each crop by the average SHFs size and multiplying it by the percentage of land allocated to SHFs. Recognizing the absence of up-to-date information, we assumed uniformity in average farm size and the percentage of SHFs across all crops. This comprehensive approach allows us to understand the critical role of smallholder farmers and tailor AI solutions to their specific needs within the selected countries.

$$\text{SHFEst} = \frac{\text{LandAll}}{\text{avgSFarm}} * \text{LASHF\%}$$

2.1 Calculating AI's Impact

To quantify the impact of Crop Protection AI on crop loss reduction (CLR), we employ a methodology where the accuracy of AI in detecting pests and diseases (AccPD), which we estimate to be at 93%,[172] is multiplied by an assumed preventable crop loss of 20% (PCL).[173] This result is further multiplied by the national average yield in tons per hectare (Yield)[174] for the given crop, providing an insightful estimate of the potential contributions of AI in mitigating crop losses for SHFs.

$$\text{CLR} = (\text{AccPD} * \text{PCL}) * \text{Yield}$$

2.2 Defining Scalable AI

A holistic evaluation of the main agriculture AI services available to farmers revealed that Crop Protection AI (which combines pest and disease management and some agronomic advisory) is the most adoptable by SHFs in SSA. For a more in-depth description of our analysis, please see the table below or refer to the full list of AI categories covered in the following *link*.

Scalable AI Matrix

Type of AI	Ease of Implementation	High impact
Pest and disease management	True	True
Agronomic Advisory	True	True
Crop monitoring	False	True
Soil Health, Nutrition management, and irrigation scheduling	False	True

In this chart, high impact is measured by the number of crops easily covered by at least one AI solution in each category. This approach is justified by the prevalent practice of intercropping among smallholder farmers in Sub-Saharan Africa. Ease of implementation takes into consideration whether the AI application represents low or high barriers to adoption depending on SHFs digital context.

3.1 Estimating Probability of Adoption

To gauge the technological impact accurately, we utilized GSMA's smartphone adoption percentage of total connections (SPA),[175] coupled with Findex's data on adults who engaged in digital payments in both rural (RurDPay) and urban (UrbDPay) areas.[176] Our assumption is grounded in the belief that rural dwellers with smartphone ownership and digital payment activity are better positioned to adopt the proposed technology. For the purposes of this study, we equate SHFs adoption with rural adoption. We used the East African Community average as a proxy for Rwandan and Ugandan connectivity, and we used Findex's poorest 40% and richest 60% to estimate RurDPay and UrbDPay values for Ethiopia and Rwanda.

We gauge technological impact at three different levels of adoption: scenario 1 ($ProbAdopt_1$), which is considered the status quo and which strictly evaluates AI uptake under current circumstances; scenario 2 ($ProbAdopt_2$), which constitutes an increase in AI uptake due to soft policy intervention; and scenario 3 ($ProbAdopt_3$), which quantifies AI's impact if the probability of adoption increases through hard, rigorous, and holistic policy interventions.

- **Scenario 1 ($ProbAdopt_1$)** represents the current state of affairs, akin to the status quo. In this context, we make an assumption that SHFs adoption of AI for crop loss reduction mirrors the patterns observed in rural adoption of smartphones for making or receiving digital payments. Within this scenario, we posit that every SHFs utilizing a smartphone for digital payment possesses both the means and willingness to adopt AI solutions aimed at safeguarding crops from pests and diseases. This is calculated by multiplying smartphone adoption by rural digital payments.

  $ProbAdopt_1$ = (SPA * RurDPay)

- **Scenario 2 ($ProbAdopt_2$),** termed the "soft lever," assesses the potential impact of AI when the SHFs adoption rate is elevated to urban rates of digital payments made from smartphones. This adjustment is achieved through the implementation of policy recommendations outlined on page 90 of this report.

  $ProbAdopt_2$ = (SPA * UrbDPay)

- **Scenario 3 ($ProbAdopt_3$)**, referred to as the "hard lever," evaluates the potential impact of AI on SHFs under the assumption that all rural dwellers currently utilizing digital payment methods can transition to smartphone usage. This scenario envisions a comprehensive policy implementation aimed at facilitating the widespread adoption of smartphones among rural communities, with the intent of maximizing the reach and effectiveness of AI solutions for SHFs.

  $ProbAdopt_3$ = (100% * RurDPay)

After the three scenarios are calculated, we use our Progress to Digital Parity: Gender (PDP) score and the percentage of women (WFarm%) and men (MFarm%) SHFs[177] in each country to understand the gender distribution of adoption by SHFs across all seven countries. This was done by using the following formula:

$$WProbAdopt_x = \frac{ProbAdopt_x}{(WFarm\% + (1 + (1 - PDP)) * MFarm\%)}$$

These calculations yield the table below, which shows each scenario of adoption nuanced by gender and the country average.

Lastly, to calculate the gender gap in adoption (GGAdopt), we subtracted the women ($WProbAdopt_x$) from the man ($MProbAdopt_x$) probabilities of adoption:

$$GGAdopt = WProbAdopt_x - MProbAdopt_x$$

Country	$ProbAdopt_1$			$ProbAdopt_2$			$Prob\ Adopt_3$		
	$WProbAdopt_1$	$MProbAdopt_1$	$ProbAdopt_1$	$WProbAdopt_2$	$MProbAdopt_2$	$ProbAdopt_2$	$WProbAdopt_3$	$MProbAdopt_3$	$ProbAdopt_3$
Côte d'Ivoire	19%	27%	24%	24%	34%	30%	34%	48%	43%
Ethiopia	4%	6%	5%	7%	12%	11%	9%	15%	13%
Kenya	31%	37%	34%	36%	44%	40%	67%	81%	74%
Nigeria	8%	12%	11%	14%	20%	18%	18%	27%	24%
Rwanda	8%	12%	10%	17%	25%	21%	20%	29%	24%
Tanzania	17%	24%	20%	22%	32%	27%	37%	53%	45%
Uganda	22%	27%	24%	26%	33%	29%	52%	65%	58%

3.2 Calculating Revenue Increases

We quantify the country-wide revenue improvements derived from AI implementation and measure the economic impacts at three different levels: Economy-Wide (EcWideRIx), Farmer-Wide (FarmerRI), and Individual Farmer (SHFRevPC) Revenue Increases. Note: all three measures are based on a single planting cycle. While some crops only have one planting cycle per year, some other crops with shorter planting cycles can have multiple planting cycles. The following variables are important for all three calculations, and need to be calculated for each individual crop of the five chosen per country for our analysis:

- **Crop Loss Reduction (CLR):** as detailed in Appendix 2.1, crop loss reduction enables us to understand how much more crop can be harvested if farmers use Crop AI to diagnose and treat crops that would otherwise be lost to pests and diseases.
- **Land Allocated to Smallholder Farmers (LASHF%):** to determine what the total CLR is at the national level, we multiply the CLR per hectare by the amount of land cultivated nationally by SHFs (LASHF%) for the top five crops. The formula can be found in Appendix 1.3.
- **Probability of Adoption ($ProbAdopt_1$, $ProbAdopt_2$, $ProbAdopt_3$):** The probability of adoption enables us to understand how much of the LASHF% will benefit from CLR as a result of AI uptake. Refer to Appendix 3.1 for methodology on how we calculate each level of adoption.
- **Export Prices (avgExP):** to estimate an accurate price range, we calculate the 10-year average (P_{2011} to P_{2022}) of the export prices for each country's top five crops.[178] This is done after removing the outlier years, which we determine by calculating each price's z-score and standard deviation and removing any price with a z-score greater or less than 3.

$$AVGExP = \frac{(P_{2011} + \ldots + P_{2022})}{n_{years}}$$

By using this method, we assume the increased productivity as a result of adoption of the technology is sold at the 10-year average export price.

- **Producer Price (PP):** the price of the crop at the farm gate was determined as 24% of the export prices of the crop. This was based on previous literature that found that between 15% to 33% of the retail price of maize got to maize farmers in Kenya and Uganda, respectively.[179] We believe this closely mirrors the reality of the other countries and crops studied herein, and we therefore chose the mid-point. Thus, the producer price is calculated as the following:

$$PP = (avgExP * 24\%)$$

- **Gross Yield Increase (GYI_x):** this statistic tells us what the nation-wide increase in yield is due to SHFsAI uptake. We determine GYI by multiplying the total crop loss reduction per hectare (CLR, Appendix 2.1) derived from AI's usage by the amount of hectares being farmed by SHFs (LASHF, LASHF%) who adopted the tech ($ProbAdopt_x$, Appendix 3.1). This is summarized in the following formula:

$$GYI_x = ([\{LandAll * LASHF\%\} * ProbAdopt_x] * CLR)$$

The amount of farmers adopting the tech will vary by scenario (1, 2, or 3), which means there are three GYI considered for each crop. Thus, in this formula, x represents the probability of adoption that is being considered, which is contingent on the hypothetical level of policy intervention.

All components mentioned hereabove are crucial to calculating the three levels of revenue increases. They are used in the following way for each measurement:

Economy-Wide Revenue Increase (EcWideRI$_x$): this measurement enables us to understand AI adoption's macro-economic impact. We determine the Economy-Wide Improvement by using the following formula:

EcWideRI$_x$ = GYI$_x$ * avgExP

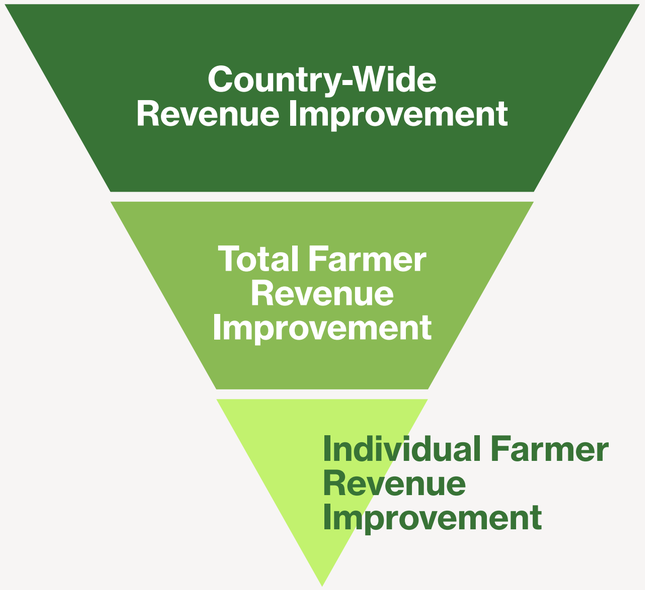
In this calculation, x represents one of the three probabilities of adoption we are using.

Farmer-Wide Revenue Increase (FarmerRI): this measurement gives us an insight into how much of the total money mentioned above is kept strictly by farmers. Similar to EcWideRI, we use the GYI to determine farmer revenue. However, instead of multiplying it by the AVGExP, we multiply it by the PP, signalling that it only accounts for the money kept by farmers:

FarmerRI = GYI$_x$ * PP

Farmer Revenue Increase per Capita (SHFRevPC): this number represents the revenue improvement at the most micro level: economic benefit to each individual farmer per planting cycle. It is calculated by multiplying the crop loss reduction (CLR) per hectare (in t/ha) by the country's average SHFs size (avgSFarm). The revenue improvement is afterwards calculated by multiplying the crop loss reduction per farm by the producer price (PP) as follows:

SHFRevPC = (CLR * avgSFarm) * PP



3.3 Calculating Gender Gap and Women Parity Revenue Increases

Understanding gender disparities in revenue increases resulting from uneven AI adoption is a central part of this report's analysis. To understand how many more women would adopt AI (GGap) if women and men had the same adoption rates, we multiply the gender gap in adoption ($GGAdopt_x$, Appendix 3.1) by the estimated number of farmers (SHFEst):

GGap = GGAdopt * SHFEst

This number is rounded to the nearest whole number and then multiplied by the average individual farmer revenue (SHFRevPC) increase to understand what the macro-economic impact would be if the gender gap is closed (WParityRI):

WParityRI = GGap * SHFRevPC

4.1 Calculating Policy Progress and Priorities

We used the following proxies to determine policy priorities:

- Trust in Technology: Findex's rural digital payments.[180]
- AI Culture Development: State of AI in Africa Report's Companies that Specialize in AI by country (per million people).[181]
- Overall Smartphone Adoption: GSMA's Mobile Economy Report.[182]
- Rural Internet Access: Euromonitor's population using the internet,[183] from which we deduced the rural penetration by using each country's *Progress to Digital Parity* Score.
- Rural Electrification: World Bank's Rural Access to Electricity.[184]
- Functional Literacy Enhancement: World Bank's Literacy Rate.[185]

Once we collected data across all categories for the seven countries studied, we normalized all scores by benchmarking them against South Africa, which is an exemplary case study in the region. Comparing each country's progress to that of South Africa allowed us to understand which countries are on par with regional expectations, which ones are excelling, and which ones are lagging.

$$\textbf{Policy Score} = \frac{(X - X_{min})}{(X_{max} - X_{min})}$$

After normalizing the scores, we divided each countries performance in each policy priority in five different categories, ranging from worst to best performance.

Côte d'Ivoire

	Scenario 1	Scenario 2	Scenario 3
Revenue Improvement	$113.1 million	$142 million	$202 million
Contribution to Agri GDP	0.96%	1.20%	1.74%
No. of SHFs impacted	369,732	464,315	660,236
Women SHFs impacted	105,585	132,595	188,544

Kenya

	Scenario 1	Scenario 2	Scenario 3
Revenue Improvement	$414.9 million	$487.8 million	$901.9 million
Contribution to Agri GDP	3.44%	4.06%	7.50%
No. of SHFs impacted	1 million	1.2 million	2.2 million
Women SHFs impacted	473,250	556,388	1,028,804

Ethiopia

	Scenario 1	Scenario 2	Scenario 3
Revenue Improvement	$159.2 million	$311.2 million	$370.3 million
Contribution to Agri GDP	0.77%	1.49%	1.78%
No. of SHFs impacted	218,497	427,067	508,133
Women SHFs impacted	56,283	110,008	130,890

Nigeria

	Scenario 1	Scenario 2	Scenario 3
Revenue Improvement	$1.7 billion	$2.9 billion	$3.9 billion
Contribution to Agri GDP	1.52%	2.62%	3.46%
No. of SHFs impacted	3.1 million	5.2 million	7 million
Women SHFs impacted	804,237	1,373,905	1,827,812

Rwanda

	Scenario 1	Scenario 2	Scenario 3
Revenue Improvement	$61.9 million	$126.7 million	$147.5 million
Contribution to Agri GDP	1.89%	3.82%	4.46%
No. of SHFs impacted	250,292	512,162	595,933
Women SHFs impacted	114,706	234,719	273,111

Uganda

	Scenario 1	Scenario 2	Scenario 3
Revenue Improvement	$144.8 million	$174.7 million	$344.6 million
Contribution to Agri GDP	1.33%	1.58%	3.15%
No. of SHFs impacted	730,694	881,872	1,739,747
Women SHFs impacted	346,259	417,899	824,426

Tanzania

	Scenario 1	Scenario 2	Scenario 3
Revenue Improvement	$104.1 million	$138.9 million	$231.4 million
Contribution to Agri GDP	0.58%	0.74%	1.28%
No. of SHFs impacted	690,100	920,134	1,533,556
Women SHFs impacted	286,512	382,017	636,694

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