CHAPTER 3

The Untapped Potential of Artificial Intelligence and Geospatial Technology in African Agrifood Systems

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Introduction

Africa's population is expected to rise dramatically in the coming decades, reaching between 2.5 billion and 2.6 billion persons by 2050 (Golden 2023; Zurlo et al. 2015). To feed this population, African agriculture will need to grow substantially—global analyses suggest that meeting Africa's food demand in 2050 may require on the order of a 70 percent increase in current production levels (FAO 2009). However, Africa's agrifood systems face persistent challenges, including climate change impacts, land and water scarcity, and market inefficiencies that constrain productivity and resilience. Food systems encompass all elements and activities from food production through to consumption and disposal, along with their socio-economic and environmental outcomes (Schulte et al. 2020). Strengthening Africa's food systems is thus central to achieving the UN Sustainable Development Goals (SDGs), notably SDG2 on zero hunger. The 2021 United Nations (UN) Food Systems Summit called for urgent systemic shifts in how food is produced, processed, and consumed globally in order to achieve hunger and environmental goals (UN 2023).

In recent years, governments and projects have begun introducing digital and geospatial tools into African agriculture. Countries like Kenya and Ghana have piloted market information and e-extension platforms, while Rwanda has developed digital fertilizer-subsidy systems. The African Continental Free Trade Area (AfCFTA), now ratified by nearly all African countries, aims to reduce trade barriers and boost intra-African agrifood trade in part through the deployment of digital trade platforms (World Bank 2022). However, significant gaps remain. Emerging technologies, such as satellite-enabled precision farming, machine-learning crop forecasting, and artificial intelligence-driven decision support, are increasingly recognized as essential for modern agriculture and agrifood systems; however, their deployment in Africa remains limited (UN 2023).

This chapter examines the untapped potential of artificial intelligence (AI) and geospatial technology in African agrifood systems. We first review key advances in AI and remote sensing relevant to agriculture. We then introduce a multidimensional untapped potential index (UPI), which assesses each country's readiness, needs, data infrastructure, policy support, and current adoption of AI and geospatial tools. Using this framework, we identify where the largest opportunities lie. The chapter concludes with a discussion of the policies required to harness these technologies to improve food security across Africa.

AI and Geospatial Innovations for Agriculture

Driven by AI and geospatial tools, there have been rapid advances in precision agriculture in recent years. Satellite and aerial (drone) imagery can now provide frequent, detailed data on crop health, soil conditions, and weather (Inoue 2020). Free global satellite-based earth observation programs, such as Landsat and Sentinel, enable researchers worldwide to monitor vegetation indices, detect nutrient deficiencies, and map water stress across large areas (Liu et al. 2020). Satellite and hyperspectral data can now be used to predict yields for crops such as wheat, maize, citrus, and sugarcane with high accuracy (Ali et al. 2022). Satellite imagery can also be used to identify water stress in plants before visible symptoms emerge (Wang et al. 2024). These capabilities are now being utilized to support systems that provide early warnings of drought or pest threats, enabling precision input management, such as variable-rate fertilizer application.

Machine learning methods transform these large datasets into actionable insights (Waqas et al. 2025; McQueen et al. 1995). Supervised learning algorithms, which train on labeled examples, are widely used in agriculture (Feng, Huang, and Chi 2020). For example, decision trees (Bishnoi and Hooda 2022), support-vector machines (Kok et al. 2021), random forests (Ok, Akar, and Güngör 2012), and neural networks (Kujawa and Niedbała 2021) have been applied to tasks that include classifying crop types from satellite imagery, segmenting fields by soil quality, and diagnosing plant diseases from the spectral signature of plant leaves in satellite images. By contrast, unsupervised learning, including clustering and dimensionality reduction, is used to uncover patterns in unlabeled data. An example of the application of such methods is grouping fields by similar yield trends or soil properties (Aghababaei et al. 2023). Deep learning, a subset of machine learning, involves neural networks with many layers. Convolutional neural networks (CNNs) (Kamilaris and Prenafeta-Boldú 2018) excel particularly at image analysis. CNNs have revolutionized the interpretation of remotely sensed images, including land-cover mapping and automated disease detection (Ball, Anderson, and Chan 2017). Similarly, recurrent neural networks (RNNs) have proven valuable for time-series forecasting, as these methods can capture seasonal or weather-related changes (Ndikumana et al. 2018).

These AI and other approaches to interpreting remotely sensed images are already making an impact. In the United States, for example, Khaki et al. (2020) developed a CNN-RNN model to predict corn and soybean yields across the Corn Belt. Their model, using historical weather and remote-sensing data, achieved a root-mean-square error of between 8 and 9 percent of average yield, which was a significantly better performance than conventional methods (Khaki, Wang, and Archontoulis 2020). In Asia, smartphone applications like Plantix leverage AI to improve plant health. Plantix uses CNNs trained on millions of annotated plant images to diagnose nutrient deficiencies and diseases from photos. Field trials in India and Vietnam report between 85 and 90 percent accuracy in disease diagnosis using such image-based tools (Maitra and Damle 2024). These applications also provide tailored treatment advice, effectively extending agronomic expertise to smallholders.

In Africa, similar innovations are emerging. The Africa Agriculture Watch (AAgWa) platform integrates satellite climate data and machine learning to provide forecasts and reduce uncertainty in decision-making for food production systems across several African countries (AKADEMIYA2063 2025). The Digital Green initiative has combined sensor data with community-based video platforms to provide farmers in Kenya and Ethiopia with advice on soil nutrients. Other drone and sensor startups across Africa are using image analysis for weed detection, irrigation management, and field-level crop health monitoring. Each example demonstrates how AI and geospatial tools are being adapted to local needs.

Despite these advances, adoption is not uniform. Major barriers persist in many countries. Connectivity remains limited—only about 25 percent of Africans south of the Sahara had mobile internet access by 2022 (GSMA 2023), which constrains data collection and application usage in rural areas. Electricity supplies, data storage, and computing infrastructure are uneven. There are also human-capital gaps. Relatively few computer scientists and agronomists in Africa are trained in AI, and many smallholders lack digital skills. Finally, financing is scarce, as governments often allocate little to the extension of such innovations, and private investment in African agrifood technologies is concentrated in a few hub economies. These barriers motivate the systematic assessment here of where Africa's foundations and needs for AI and geospatial technology are strongest, and where the untapped potential is greatest.

Framework for Assessing Potential

To quantify each country's opportunity to leverage AI and geospatial solutions, we develop a composite untapped potential index (UPI). To our knowledge, this is the first time this approach has been applied to this type of study. The UPI score reflects a country's potential to leverage AI and geospatial solutions in its agrifood system, based on its readiness and need, minus its current adoption of these technologies. A higher UPI indicates a stronger untapped opportunity, suggesting strong foundations and high need with limited existing deployment. Our framework uses five key dimension indicators, each computed from five parameters. (Also see Table 3.1.)

Digital and AI readiness. This dimension measures technological capacity and the innovation environment. The parameters used to compute it include the existence of a national AI or digital agriculture strategy, internet and mobile penetration rates, the number of AI or data science training programs nationally,

BOX 3.1—IMPLICATIONS FOR POLICY AND PRACTICE

Developing dedicated AI and geospatial technology policies tailored to the agrifood sector is a crucial step toward enabling the digital transformation of the sector. Such policies provide a clear roadmap for integrating advanced technologies into agrifood systems, outlining strategic priorities, regulatory frameworks, ethical considerations, and investment plans. They also help align efforts across ministries and agencies, ensuring coherence between agricultural development goals and national digital strategies. Tailored policies can address sector-specific challenges, such as data access for smallholder farmers, digital literacy, and the deployment of precision agriculture tools, making it easier to scale solutions that are both impactful and inclusive.

In parallel, strengthening regional collaboration and data-sharing initiatives is essential to maximize the benefits of AI and geospatial technologies. Many agricultural challenges, such as climate variability, cross-border pests, and food insecurity, transcend national boundaries, making collective action critical.

and the number of AI startups involved in the country's agrifood sector. For example, a government that has implemented a formal AI strategy earns points, as do countries with high broadband coverage or active technology hubs.

Agrifood system transformation needs. This dimension captures the urgency with which a country needs to transform its agrifood system. Key parameters used in its computation are agriculture's share of national employment and GDP, yield gaps for the country's staple crops, the prevalence of hunger or malnutrition in the population, and climate vulnerability as measured by exposure to climate-related shocks. In most African countries, agriculture typically employs approximately 65 percent of the workforce and contributes between 30 and 40 percent of GDP (World Bank 2013). Countries with populations heavily dependent on agricultural livelihoods and that exhibit significant deficits in staple crop yields relative to potential yields tend to score high on this dimension. It is in these countries that the increased application of AI and geospatial technologies in the agrifood sector could potentially have the most significant impact on livelihoods and agricultural productivity.

Geospatial and data infrastructure. The availability of spatial and digital data resources is assessed in this dimension. The parameters used to create it include the existence of a national geospatial and mapping agency, open agricultural data portals, access to earth-observation platforms, participation in international geospatial initiatives such as GEOGLAM and AfriGEO, and the routine use of GIS for land and agricultural field monitoring. These factors determine whether satellite and sensor data can be effectively used in farming decisions.

Policy, institutional, and financing enablers. This dimension evaluates the broader ecosystem for digital agriculture. The underlying parameters include the adoption of a national digital economy or e agriculture strategy, public investment in digital-agriculture projects, the presence of innovation hubs or technology incubators focused on agriculture, the existence of data governance or open-data policies, and the level of public-private partnership activity in making use of AI or remote sensing technologies for farming. Countries with clear policies and funded programs score higher, reflecting an environment that supports technology diffusion.

Current AI and geospatial adoption. The on-the-ground use of AI or remote sensing technologies in a country's agrifood system is measured in this dimension. We count the number of recent scientific publications on AI or remote sensing in agriculture, the number of active AI or remote sensing projects, whether public or private, the extent of AI-based advisory services to farmers, the share of farmers reached by digital platforms, and the degree to which satellite-based monitoring is integrated into national food security systems. A high score means the country already has an active community of users and projects in its agrifood sector, which tends to narrow the untapped gap.

Table 3.1 presents the scoring scheme used to assign values to each parameter that contributes to the overall score for the five dimensions of UPI. Each parameter is represented by an abbreviated form of its full name, providing a concise, standardized representation across the table. Each parameter was scored on a five-level scale, but generally employs scores of 0, 3, or 5. The scores are based on defined thresholds or binary conditions. This scheme ensures consistency in how the different parameters are evaluated within each dimension. The indicator score for a dimension is obtained by averaging its five parameter scores. The UPI is then calculated using the following steps.

Step 1: Parameter scoring

The detailed approach for the dimension indicator scoring is described in Table 3.2. The general rule used to provide a threshold-based method for translating values of parameter p into standardized scores is in the form of the expression, 0: $p<a$; 3: $a \leq p<b$; 5: $p\geq b$, where :

- A score of 0 is assigned if $p<a$, indicating a *very low level* of performance.
- A score of 3 is assigned if $a\leq p<b$, indicating a *moderate potential level*.
- A score of 5 is assigned if $p\geq b$, reflecting a *high level* of performance.

Here, a, b, and c are some constants, as can be seen in Table 3.1.

A binary scoring approach is used for some parameters, where:

- A score of 0 is assigned if the parameter does not meet a specific condition, mainly the absence of a policy or system, and
- A score of 5 is assigned if the parameter meets the condition, reflecting full compliance or presence.

TABLE 3.1—UNTAPPED POTENTIAL INDEX (UPI) DIMENSION PARAMETERS WITH SCORING RULES

Dimension	Parameter	Scoring rule
Digital and AI readiness (DIVA)	National AI strategy presence	0: No; 3: Draft; 5: Implemented
	Internet penetration rate (IPR), %	0: IPR < 10; 3: 10 ≤ IPR < 70; 5: IPR ≥ 70
	Mobile phone penetration (MPP), %	0: MPP < 50; 3: 50 ≤ MPP < 90; 5: MPP ≥ 90
	AI training programs (NTP), number	0: NTP = 0; 3: 1 ≤ NTP < 4; 5: NTP ≥ 4
	AI startups/companies (NSC), number	0: NSC < 2; 3: 2 ≤ NSC < 10; 5: NSC ≥ 10
Agrifood system transform-ation needs (DIVB)	Agricultural labor share (AgLS), %	0: AgLS < 10; 3: 10 ≤ AgLS < 50; 5: AgLS ≥ 50
	Yield gap (YG), %	0: YG < 10; 3: 10 ≤ YG < 60; 5: YG ≥ 60
	Food insecurity prevalence (FIP), %	0: FIP <5; 3: 5 ≤ FIP < 35; 5: FIP ≥ 35
	Exposure to climate shocks (ECS)	0: ECS = Low; 3: ECS = Moderate; 5: ECS = High
	AgGDP as percentage of GDP, %	0: AgGDP < 5; 3: 5 ≤ AgGDP < 25; 5: AgGDP ≥ 25
Geospatial and data infra-structure (DIVC)	Existence of a national geospatial agency	0: No; 5: Functional agency that shares data
	Access to earth observation (EO) satellite data platforms	0: No; 5: Active EO data users nationally
	Existence of national agricultural data portals	0: No; 5: Operational and open-access portals
	Participation in global EO Initiatives	0: No; 5: Member of GEO, AfriGEO, and GEOGLAM
	Use of GIS in land or crop monitoring	0: No; 5: Operational in land use, crop, and forest monitoring
Policy, institutional, and financing enablers (DIVD)	Digital economy strategy adoption	0: No policy, 5: Policy includes agriculture, AI, or remote sensing
	Public investment in digital agriculture	0: No, 5: Projects funded and implemented
	Existence of innovation hubs (EIH)	0: EIH = 0; 3: 1 ≤ EIH < 4; 5: EIH ≥ 4
	Data policy frameworks	0: No policy, 5: Comprehensive and enabling
	Public-private partnerships (PPP) in AI or remote sensing in agriculture	0: None, 5: Multiple PPPs
Current AI and geospatial technology adoption (DIVE)	Published research (PR) using AI or remote sensing in agriculture	0: PR < 5; 3: 5 ≤ PR < 30; 5: PR ≥ 30
	Active AI or remote sensing projects in agriculture (AP)	0: AP = 0; 3: 1 ≤ AP < 10; 5: AP ≥ 10
	Use of AI in agricultural advisory service provision	0: No, 5: Apps or other platforms used by farmers
	Digital farmer coverage (DFC)	0: DFC < 5; 3: 5 ≤ DFC < 50; 5: DFC ≥ 50
	Remote sensing methods used in food security monitoring	0: No, 5: Fully integrated into national systems

Source: Authors' compilation.
Note: Data were collected from different sources for different years.

Step 2: Dimension indicator scoring

Each of the five-dimension indicators is computed from five parameters. To compute the dimension indicator scoring value (DIVd) of dimension d, a simple average of the five parameter (p) scores is used:

$$\mathrm{DIV_d} = \frac{\sum_{p=1}^{5} p_d}{5}$$

where p_d are the parameters within the dimension indicator d.

This results in five-dimension indicators per country, which are denoted as:

- $\mathrm{DIV_A}$: Digital and AI readiness dimension indicator
- $\mathrm{DIV_B}$: Agrifood system transformation needs dimension indicator
- $\mathrm{DIV_C}$: Geospatial and data infrastructure dimension indicator
- $\mathrm{DIV_D}$: Policy, institutional, and financing enablers dimension indicator
- $\mathrm{DIV_E}$: Current AI and geospatial adoption in agrifood systems dimension indicator

Step 3: Untapped Potential Index computation

The Untapped Potential Index (UPI) is designed to identify gaps between a country's potential to utilize AI or remote sensing technologies in its agrifood system—reflecting its readiness, needs, infrastructure, and support systems for these technologies—and its current level of technology adoption. It is calculated as the average of the first four-dimension scores minus the score of the current adoption dimension:

$$\mathrm{UPI} = \frac{\mathrm{DIV_A} + \mathrm{DIV_B} + \mathrm{DIV_C} + \mathrm{DIV_D}}{4} - \mathrm{DIV_E}$$

The UPI index formula quantifies how much potential remains untapped in each country. A positive UPI indicates more potential than current adoption. In practical terms, the UPI highlights countries with strong infrastructure and acute needs that have not yet extensively deployed AI and geospatial technologies in their agrifood systems. Thus, the UPI framework, based on measurable dimension indicators, provides a data-driven way to benchmark countries and identify where targeted interventions, such as policy reform, training, and investment, can have the greatest effect. The following section presents the results and insights from the classification of African countries based on the UPI index.

Untapped Potential Index (UPI) Results Analysis

Applying this framework to available data for African countries yields considerable variation in readiness, needs, and adoption levels of AI and geospatial technologies. The maps in Figures 3.1 to 3.5 display the scores for each UPI dimension indicator. Figure 3.6 shows the resulting UPI values.

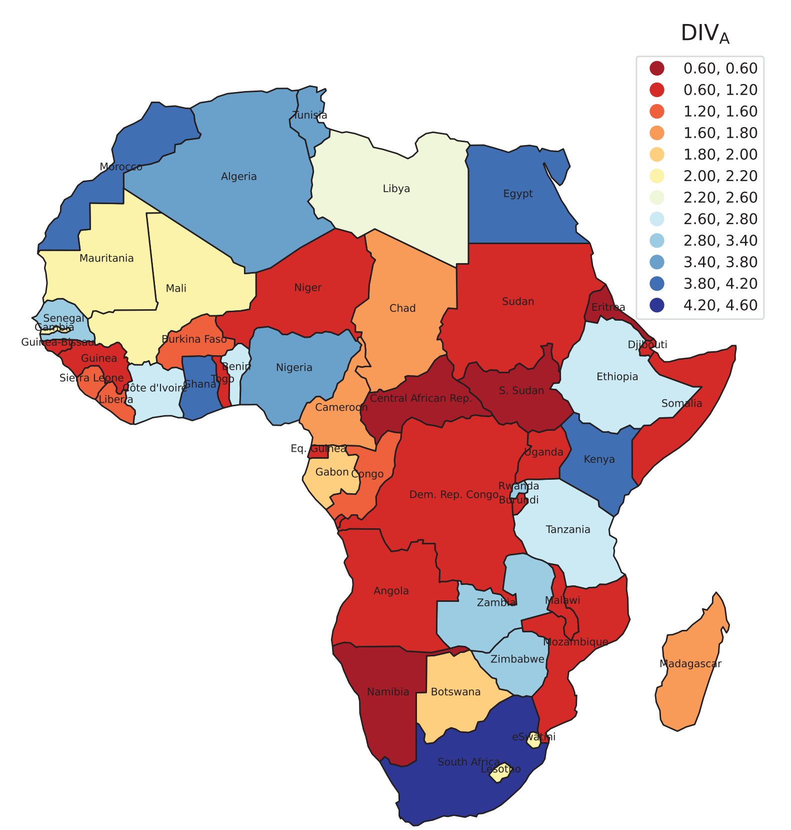
Digital and AI readiness dimension indicator

DIVA measures a country's readiness for AI and remote sensing technology adoption within its agrifood system. A high DIVA score indicates robust backing from national authorities, evidenced by a formal AI or digital agriculture strategy at the governmental level, widespread internet and mobile connectivity, good availability of local technical expertise, and a vibrant ecosystem of AI startups dedicated to agrifood systems.

Figure 3.1 maps the DIVA scores for African countries. In this figure, countries with high readiness scores between 2.6 and 4.6 (in blue) have strong digital infrastructure, well-established national AI strategies, and local technical expertise available. Countries with moderate readiness scores between 1.8 and 2.6 (in yellow) show some progress but also persistent gaps in areas such as governance or capacity. Major challenges, including weak internet connectivity, limited technical capacity, and underdeveloped policy environments, characterize countries with low readiness with scores below 1.8 (in red).

The results show that northern and southern African countries generally show the highest readiness scores. For example, Egypt, South Africa, Tunisia, and Morocco have national AI or digital strategies and relatively high internet and mobile penetration, placing them near the top of this dimension indicator. Middle-performing countries, like Ghana, Kenya, and Nigeria, have growing technology sectors and improving connectivity. By contrast, many Sahelian and other landlocked countries lack formal AI policies and have low internet coverage, resulting in low readiness scores.

FIGURE 3.1—DIGITAL AND AI READINESS DIMENSION INDICATOR (DIVA) FOR AFRICAN COUNTRIES



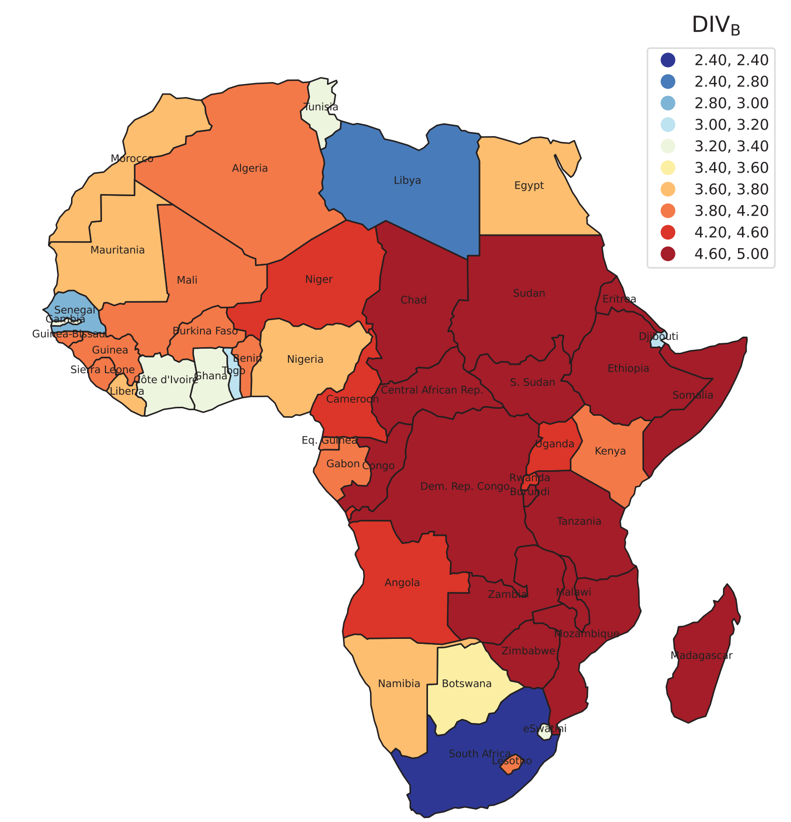
Source: Authors' compilation.

Agrifood system transformation needs dimension indicator

The agrifood system transformation needs dimension indicator (DIVB) highlights why a country's agrifood system requires the adoption of AI and geospatial technologies to drive meaningful change. Figure 3.2 maps the DIVB computed for the African countries. Using this dimension indicator, countries with higher scores are those where agriculture constitutes a large share of employment and GDP, yet faces low productivity, persistent hunger, food insecurity, and climate-related risks.

This map shows that almost all African countries score high (yellow to red) on this dimension indicator, reflecting the continent's urgent agricultural challenges. While agriculture remains the primary source of livelihood for the majority of the population, yields of staple food crops are far below their potential. For example, countries such as Niger, Chad, and South Sudan have some of the highest rates of chronic food insecurity and are particularly vulnerable to climate shocks, underscoring the urgent need for innovation. In short, there is a pervasive high need for productivity gains and risk management across Africa.

FIGURE 3.2—AGRIFOOD SYSTEM TRANSFORMATION NEEDS DIMENSION INDICATOR (DIVB) FOR AFRICAN COUNTRIES

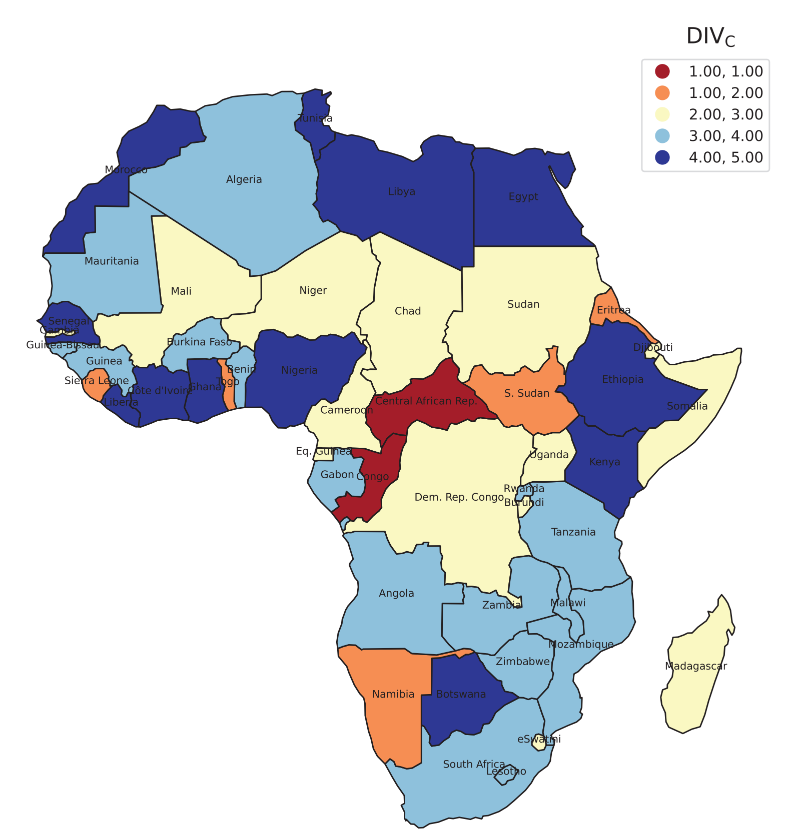


Source: Authors' compilation.

Geospatial and data infrastructure dimension indicator

The data and infrastructure dimension indicator (DIVC) measures the basic geospatial and other digital data resources vital to AI-driven agriculture. DIVC encompasses the presence of a national geospatial agency, agricultural data portals, access to earth observation platforms, engagement in global geospatial initiatives, and the application of GIS for land and crop monitoring. Countries with high scores are equipped with functioning national geospatial agencies, agricultural data portals, access to earth observation platforms, and are active participants in global geospatial initiatives.

FIGURE 3.3—GEOSPATIAL AND DATA INFRASTRUCTURE INDICATOR (DIVC) FOR AFRICAN COUNTRIES



Source: Authors' compilation.

Figure 3.3 shows the DIVC scores for African countries. Many African countries have invested in geospatial capacity. A majority possess a national mapping or geospatial agency, participate in international earth observation programs, and have open data portals for agriculture. Most African countries also have access to Earth-observation platforms, participate in global geospatial initiatives, or leverage GIS for land and crop monitoring. Countries scoring highest on this dimension (darker blue) operate well-equipped institutions and actively use GIS in agriculture, such as for routine satellite crop monitoring. Countries with lower scores either lack such agencies or have data in siloed form.

Policy, institutional, and financing enablers dimension indicator

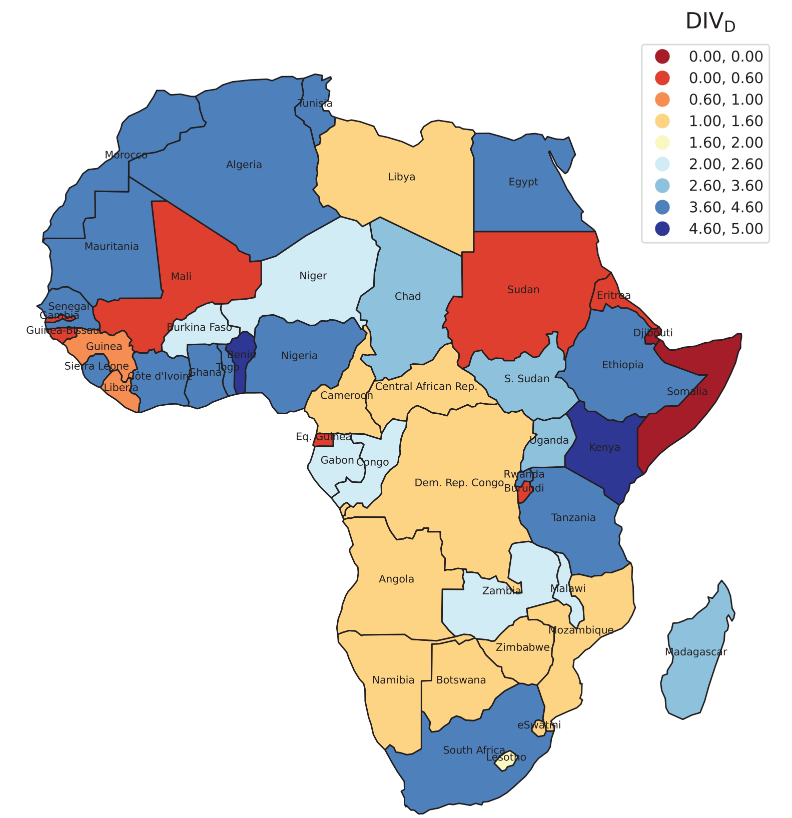
The policy, institutional, and financing enablers dimension indicator (DIVD) reflects the strength of the enabling environment for digital agriculture by tracking the presence of a national digital economy strategy, public investment in the digitization of agrifood systems, innovation hubs, data policy frameworks, and public-private partnership engagement. It highlights that effective adoption of AI and geospatial technologies depends not only on their availability but also on supportive policies, strategic investments, innovation hubs, and strong public-private partnerships. Figure 3.4 illustrates the performance of African countries on the dimension indicator DIVD.

The analysis shows that countries with strong digital agriculture-enabling environments include Kenya, Rwanda, Ethiopia, and South Africa. These countries have comprehensive digital economy or agriculture strategies that include AI and geospatial technologies and have cultivated innovation hubs and public-private partnerships. For example, Kenya and Rwanda have funded national agricultural technology challenges and incubators. In contrast, countries scoring lower are often only at the drafting stage of their digital economy policies or allocate only limited funding to digital agriculture.

Current AI and geospatial technology adoption in agrifood systems dimension indicator

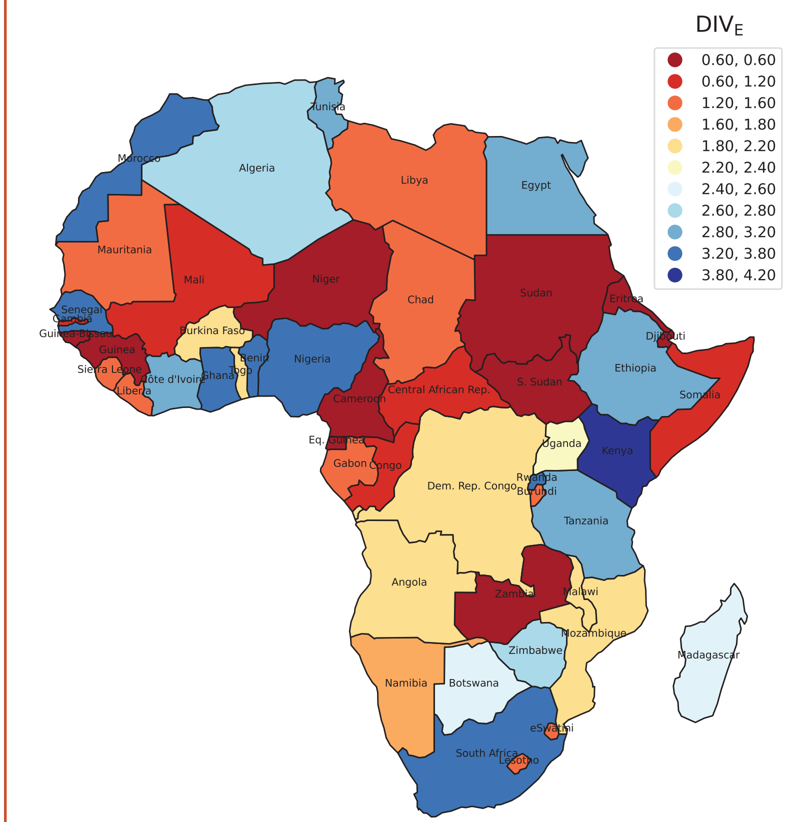
The main goal of this dimension indicator (DIVE) is to capture initiatives that reflect a country's progress and learning in the use of AI and geospatial

FIGURE 3.4—POLICY, INSTITUTIONAL, AND FINANCING ENABLERS DIMENSION INDICATOR (DIVD) FOR AFRICAN COUNTRIES



Source: Authors' compilation.

FIGURE 3.5—CURRENT AI AND GEOSPATIAL ADOPTION IN AGRIFOOD SYSTEMS DIMENSION INDICATOR (DIVE) FOR AFRICAN COUNTRIES



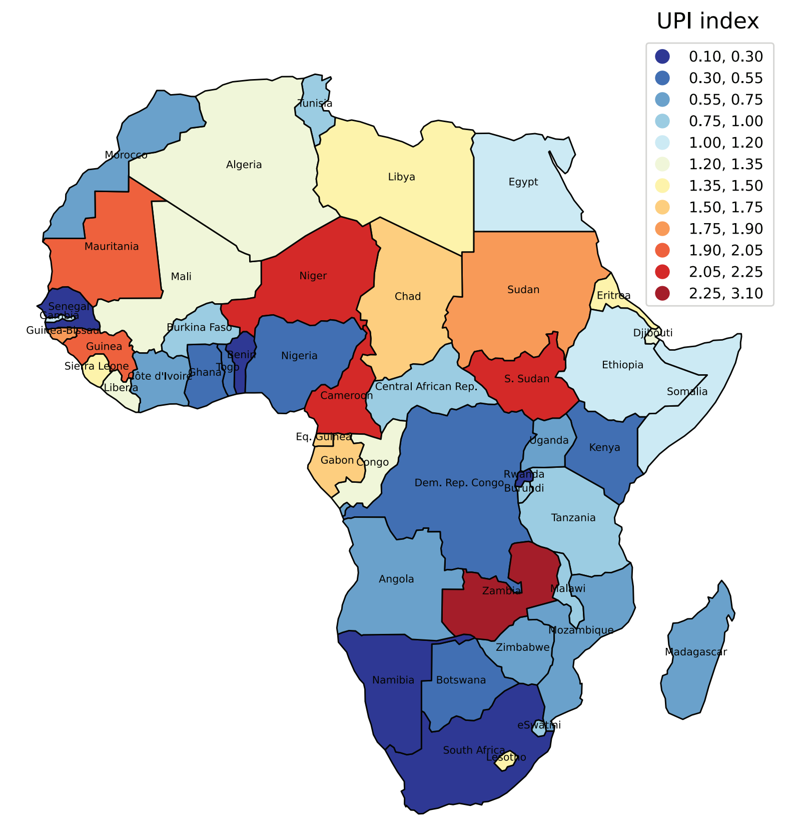
Source: Authors' compilation.

technologies. DIVE is designed to assess the extent to which AI and geospatial technologies are currently being implemented within a country's agrifood systems. The indicator captures a range of activities that reflect each country's practical engagement with these technologies. Countries with high values have made progress in adopting AI and geospatial technologies.

Figure 3.5 illustrates how DIVE varies across African countries. A few countries have reached scale in AI and geospatial adoption in their agrifood systems. South Africa, for instance, has numerous active projects, such as AI for precision irrigation and livestock monitoring. South African researchers in the field have published many scientific journal articles, contributing to a relatively high adoption score. Egypt and Nigeria also show moderate use of AI tools. However, most countries (shades of red and yellow) are at an early stage—possibly having some pilot projects or early research initiatives, but with little farmer use.

This indicator is important because it helps identify the untapped potential of AI and geospatial technologies in agriculture, highlighting the benefits countries could gain but have not yet fully realized.

FIGURE 3.6—UPI FOR AFRICAN COUNTRIES



Source: Authors' compilation.

Untapped Potential Index (UPI)

In this section, we discuss the UPI for each country as a measure of the gap between a country's potential and its actual adoption of AI and geospatial technologies in its agrifood system. A country's potential is assessed on the first four of the five key dimensions factors discussed above—readiness, transformation needs, availability of geospatial and data infrastructure, and the strength of its AI and geospatial technology support systems. A higher UPI value indicates a greater untapped potential, meaning the country has strong foundational elements but has yet to fully implement or benefit from these technologies in its agrifood system.

Combining the above, we compute the UPI for each African country, as mapped in Figure 3.6. The analysis shows that three countries stand out with the highest UPI values: South Sudan, Niger, and Zambia. These countries share a pattern of very high need, with large yield gaps and high hunger rates, decent readiness infrastructure, such as policies or good connectivity, but very low current adoption of AI and geospatial tools. For example, Zambia has a digital agriculture strategy and rapidly expanding mobile connectivity, yet almost no active precision farming projects.

In the medium-high UPI range between 1.75 and 2.25 are Sudan, Mauritania, and Chad, which similarly have supportive governance environments and acute agricultural challenges but limited scaling of innovation. Countries with a moderate UPI of between 1.00 and 1.75 include Kenya, Egypt, Ghana, and Mali. These countries have emerged with digital infrastructure and some AI projects; therefore, their adoption is closer to readiness levels. Finally, a few countries, including South Africa and Botswana, have low UPI values, indicating that their AI and geospatial technology deployment in the agrifood sector has begun to match what our indicators would predict as their potential, even if adoption is primarily in the early-adopter sectors.

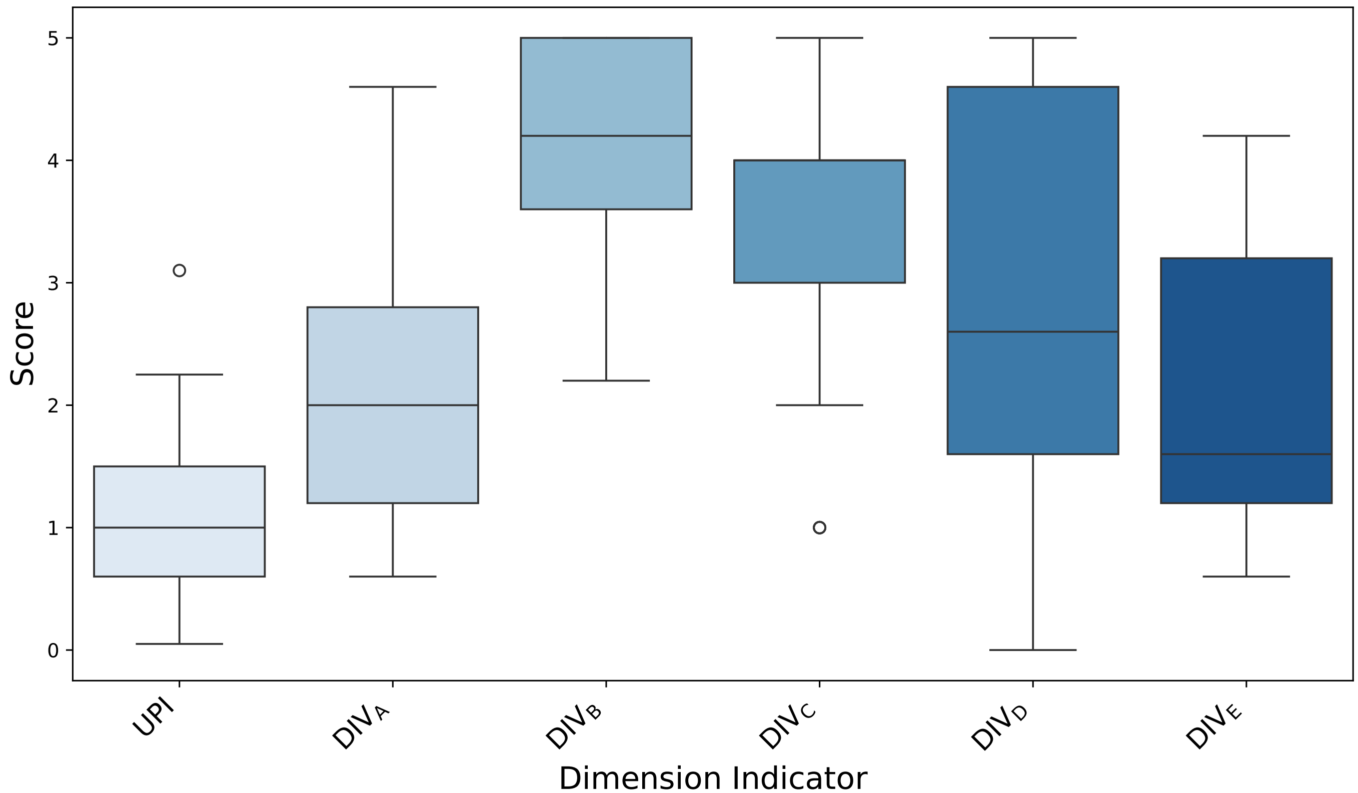
In summary, almost all African countries have high UPI scores, indicating significant untapped potential to increase the use of AI and geospatial technologies in their agrifood systems. This latent potential reflects both a pressing need, driven by challenges like yield gaps, climate risks, and market inefficiencies, and a growing readiness in terms of infrastructure, policy frameworks, and human capital. By channeling investments, fostering public-private partnerships, and scaling proven pilot projects, African countries can leapfrog traditional development pathways and harness data-driven insights to drive the growth of their agrifood sectors and enhance the livelihoods of workers and households reliant on them.

Key patterns and disparities

Understanding how the dimension indicator scores are distributed across African countries is essential for identifying key patterns, disparities, and opportunities for targeted interventions to increase the adoption of AI and geospatial technologies in agrifood sectors across the continent. Figure 3.7 presents a visual summary, highlighting the distribution and variability of scores across the five dimensions, as well as the UPI index. This visualization reveals that, while most countries score relatively high on transformation needs (DIVB), due to factors like food insecurity, climate vulnerability, and agricultural employment dependence, their current adoption levels (DIVE) often lag behind significantly. This mismatch between the need to employ AI and geospatial technology in their agrifood systems and their implementation is a primary driver of elevated UPI scores in many countries. The low disparity in UPI values suggests that most African countries share a common, untapped potential to integrate AI and geospatial technologies into their agrifood systems.

Furthermore, Figure 3.7 highlights considerable variability across the other dimension indicators, such as those for policy, institutional, and financing enablers (DIVD), as well as the current adoption of AI and geospatial technologies in agrifood systems (DIVE).

FIGURE 3.7—BOXPLOT OF UPI AND THE DIMENSION INDICATOR SCORES FOR AFRICAN COUNTRIES



Source: Compiled by authors.

Notes: Dimension indicators: DIV_A: Digital and AI readiness; DIV_B: Agrifood system transformation needs; DIV_C: Geospatial and data infrastructure; DIV_D: Policy, institutional, and financing enablers; DIV_E: Current AI and geospatial adoption in agrifood systems.The UPI outlier is Zambia. The outliers for DIV_C are Central African Republic and Congo, with the same low value.

BOX 3.2—ROADMAP FOR UNLOCKING POTENTIAL

To fully realize the transformative potential of AI and geospatial technologies in agrifood systems, African countries must pursue a strategic, multidimensional approach. This roadmap outlines three key pillars essential for enabling scalable, inclusive, and sustainable adoption of these technologies in agrifood systems: investments in infrastructure and capacity, policy and institutional support, and partnerships and innovation. To strengthen this roadmap, specific use cases need to be examined. In the future, we intend to move in this direction. At this stage, we simply provide guidance to the roadmap for researchers and decision-makers.

In some cases, countries may have strong infrastructure or supportive policies but still lack operational projects or scalable digital solutions in agriculture and, more broadly, in their agrifood system.

Conversely, a few countries, such as Namibia, with only modest infrastructure and policy support, may, nonetheless, exhibit successful early-stage adoption, possibly due to pilot programs or donor-funded initiatives. Importantly, the boxplot in Figure 3.7 captures the range, median, and outliers for each dimension. This distributional view supports the case for differentiated strategies, recognizing that no single pathway fits all countries. Tailored solutions are required to close the implementation gap and unlock the full potential of AI and geospatial technologies in Africa's agrifood systems.

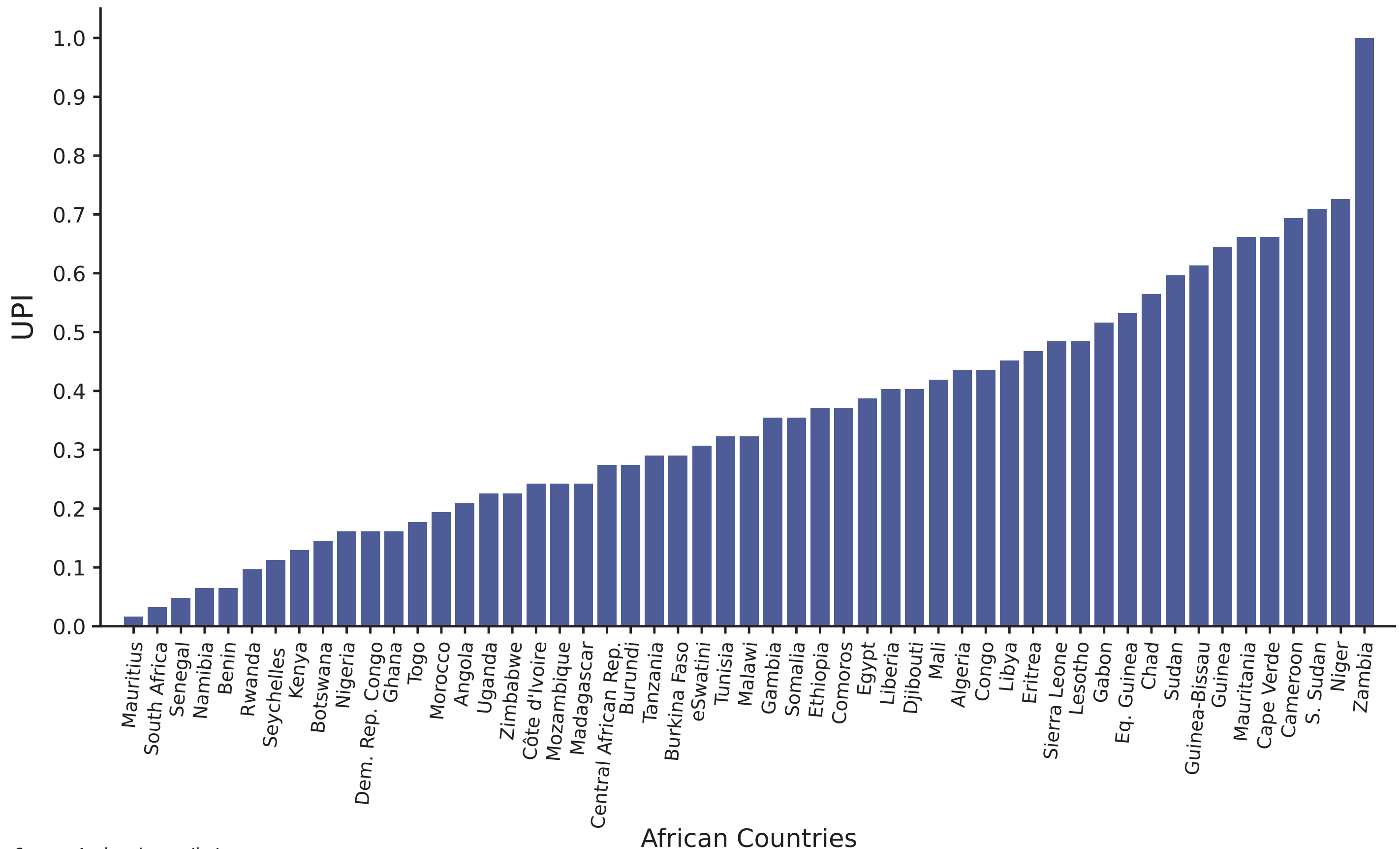
To identify the countries requiring the most support and targeted interventions, Figure 3.8 displays for all African countries their normalized UPI values—that is, scaled between 0 and 1—and arranged in ascending

TABLE 3.2—UPI-BASED CATEGORIES FOR AFRICAN COUNTRIES, WITH KEY CHARACTERISTICS AND PRIORITY INTERVENTIONS

Potential	UPI	Examples	Key characteristics	Priority intervention
High	2.25–3.10	South Sudan, Niger, Zambia	• Strong policy/infrastructure foundations	• Targeted investments in scalable AI and geospatial solutions
			• Acute transformation needs (yield gaps, climate risks)	• Capacity-building programs
			• Limited current adoption	• Public-private partnerships for tech deployment
Medium-high	1.75–2.25	Sudan, Mauritania, Chad	• Supportive governance structures	• Scale existing initiatives
			• Under-leveraged resources	• Integrate techs into standard farming practices
			• Early-stage pilot projects	• Enhance data-sharing networks
Medium	1.00–1.75	Egypt, Kenya, Ghana, Mali	• Emerging digital infrastructure	• Improve platform interoperability
			• Moderate policy support	• Expand farmer outreach
			• Fragmented adoption	• Foster innovation ecosystems beyond early adopters
Low	0.10–1.00	South Africa, Namibia, Botswana, Senegal	• Advanced tech adoption	• Regional knowledge-sharing (best practices, tech expertise)
			• Alignment between readiness and implementation	• Export scalable platform designs
			• Mature digital agriculture ecosystems	• Focus on sustainable innovation

Source: Authors' compilation.
Note: Data were collected from different sources for different years.

FIGURE 3.8—UPI SCORES OF AFRICAN COUNTRIES, ARRANGED IN ASCENDING ORDER



Source: Authors' compilation.

order. The ranking illustrates the relative untapped potential for AI and geospatial technology integration in agrifood systems across the continent. At the lower end of the scale, Mauritius emerges as the country with the least untapped potential, indicating a strong alignment between readiness for and adoption of AI and geospatial technologies in its agrifood sector. In contrast, Zambia has the highest UPI score, highlighting its significant untapped potential for adopting AI and geospatial technologies in its agrifood systems.

Table 3.2 provides a summary of the UPI rankings by grouping countries into four categories based on their UPI scores: high, medium-high, medium, and low. Key characteristics and recommended priority intervention areas for the countries in each category are also outlined. Each category reflects a different degree of readiness and potential for adopting AI and geospatial technologies in national agrifood systems.

Conclusions

The UPI analysis demonstrates that AI and geospatial technologies are highly relevant to African agrifood systems, yet they are far from being fully utilized. Applications such as satellite-driven drought forecasting, image-based pest detection, and machine-learning-driven agronomy have proven capable of boosting yields and reducing losses. Satellite early-warning systems have been shown to cut drought-induced crop losses by up to half, while precision irrigation combined with AI can reduce water use by between 20 and 40 percent. These gains remain largely theoretical in Africa's smallholder-dominated farms, creating a massive opportunity for applying these technologies to foster agrifood system development across the continent.

To realize this potential, targeted actions are needed. Policymakers should invest in building data and connectivity infrastructure, such as expanding rural internet systems and establishing open agricultural data platforms. In parallel, investments in human capacity are needed, including university programs in AI and geospatial technologies, as well as training for extension workers on how to utilize these technologies in the field. Governments and donors should focus these investments in countries with high UPI—for instance, pilot programs in Zambia or Niger could have outsized impacts, given the strong need for and readiness to adopt AI and geospatial technologies in these countries' agrifood sectors, as shown in the analysis here. At the same time, sharing knowledge across borders, such as through continental initiatives or regional hubs, can help lagging countries learn from neighbors' successes in increasing the adoption of these technologies in their agrifood sector.

For the private sector, these findings signal where demand for innovation may be most pressing. Technology companies and NGOs can use these UPI data to prioritize the deployment of AI solutions in high-gap countries. International organizations, such as AfDB, FAO, and AU, can similarly channel resources —including grants, technical support, and partnerships —to the nations and communities identified as most ripe for transformation.

In summary, African agrifood systems stand at the cusp of a digital revolution. Our framework shows that almost every country has significant untapped potential—the mix of digital readiness and deep agricultural needs is uniquely high in Africa. By strategically aligning investments, policies, and partnerships to the areas of greatest opportunity, African nations can accelerate their adoption of AI and geospatial tools in their agrifood sectors. Doing so will be critical to boosting productivity, ensuring food security, and building a resilient and sustainable agrifood sector for the future.

Appendix

Investments in infrastructure and capacity

Ensuring widespread access to robust digital and geospatial infrastructure is a foundational step toward digital agriculture. These investments include expanding broadband and mobile connectivity in rural areas, enhancing national geospatial platforms, and improving access to earth observation systems. Parallel investments in open-data portals, satellite imagery repositories, and cloud-based analytics tools are also critical for supporting real-time monitoring, forecasting, and precision agriculture services.

Building human capacity requires expanded education and training programs. Technology alone is not enough since people are at the core of successful digital transformation. Countries need to invest in developing a skilled workforce capable of designing, managing, and using AI and geospatial solutions effectively. This involves integrating digital agriculture into higher education curricula, offering vocational training for extension workers and farmers, and fostering public-private partnerships to deliver practical learning programs. Empowering youth and women with digital skills is also essential to ensure inclusive participation in the agrifood system.

Policy and institutional support

In policy and institutional support, developing AI and geospatial policies tailored to agriculture is crucial. Creating policy frameworks that explicitly address the use of AI and geospatial technologies in agrifood systems helps align national priorities and guide investment. These policies should promote the ethical use of AI, ensure data privacy, and facilitate innovation while addressing the unique challenges of agrifood systems, including fragmented data systems, interoperability gaps, and rural connectivity challenges. Tailored policies also enable coordination across the agrifood, technology, environment, and education sectors.

Another critical aspect of policy and institutional support involves strengthening regional collaboration and data-sharing initiatives. Collaboration at the regional level amplifies the impact of national efforts by fostering knowledge exchange and resource sharing. Joint initiatives can support the development of regional data platforms, harmonized data standards, and interoperable systems that benefit multiple countries. Sharing best practices, engaging in peer learning, and building regional networks of researchers, policymakers, and practitioners accelerate progress and reduce duplication. Regional cooperation also strengthens the collective ability to respond to transboundary challenges, such as climate change, pests, and food insecurity.

Partnerships and innovation

Building strong partnerships across sectors is essential for accelerating the adoption of AI and geospatial technologies in agrifood systems. The private sector, including tech companies and agricultural technology startups, brings innovation, agility, and cutting-edge solutions that can complement public initiatives. Engaging these players helps bridge the gap between research and practical application, ensuring that these technologies are scalable and market-ready. In addition, collaboration with international development partners can provide financial support, technical expertise, and global best practices, all of which enhance national efforts to modernize agrifood systems and promote sustainable development.

Innovation hubs and incubators can serve as critical engines for developing, testing, and scaling agricultural technologies. By fostering collaboration among researchers, entrepreneurs, farmers, and policymakers, these centers help transform ideas into impactful solutions tailored to local needs. They provide access to mentorship, funding, digital tools, and field-testing environments, enabling startups and innovators to accelerate the development of AI and geospatial technology applications for agriculture and the wider agrifood system.