ReSAKSS
Regional Strategic Analysis and Knowledge Support System
by AKADEMIYA2063

Annual Trends and Outlook Report 2025

MOVING THE TECHNOLOGY FRONTIERS IN AFRICAN AGRIFOOD SYSTEMS

Edited by
Christian Henning, Menale Kassie, and Racine Ly

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Established in 2006 under the Comprehensive Africa Agriculture Development Programme (CAADP), the Regional Strategic Analysis and Knowledge Support System (ReSAKSS) supports efforts to promote evidence- and outcome-based policy planning and implementation. In particular, ReSAKSS provides data and related analytical and knowledge products to facilitate CAADP benchmarking, review, and mutual learning processes. AKADEMIYA2063 leads the work of ReSAKSS in partnership with the African Union Commission, the African Union Development Agency-New Partnership for Africa's Development (AUDA-NEPAD), and leading regional economic communities (RECs). AKADEMIYA2063's mission is to provide data, policy analysis, and capacity strengthening support to enable African Union (AU) Member States to achieve economic transformation and shared prosperity in support of the AU's Agenda 2063.

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CHAPTER 16

From Innovation to Impact: Exploring the Economic Potential of Digital Twins in European and African Agriculture

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Introduction

In Asia and Latin America, impressive examples of successful promotion of inclusive economic growth through increased agricultural productivity can be observed (Henning et al. 2025). In Africa South of the Sahara, improving agricultural productivity has also become an important strategy for reducing poverty, enhancing inclusive growth, and promoting structural transformation. It is nevertheless fair to conclude that African countries have not yet unlocked the full potential of their agrifood systems, not only as engines of economic growth but also as pillars of resilience, equity, and ecological stewardship. Ultimately, unlocking Africa's agricultural transformation demands smart technologies.

In this context, this section analyzes the extent to which innovative digital twin (DT) technologies could be among the smart technologies that help Africa eliminate hunger and poverty. Digital twin technologies combine artificial intelligence (AI)-based weather forecasts and biophysical data with crop modeling and are increasingly being applied in agriculture in the European Union (EU).

The chapter is structured as follows. In the next section, we provide an overview of modeling and digital twinning, beginning with a digital twin for potatoes currently being tested in the Netherlands. In section 3, we discuss whether digital twin technology can be leveraged to manage agricultural production in Africa, taking groundnut production in Senegal as an example. We also describe the actions needed to create a digital twin for groundnuts and the available resources that could be used. Assessing the potential of smart crop technologies, however, is not just a technical question for crop science research; rather, it requires a broader analysis of economic responses at the farm level, as well as an investigation of the resulting economy-wide adaptation processes and feedback loops. In section 4, we present studies that model the potential impact of DT technologies on economic performance at the micro level of individual farms. We also discuss how these micro-economic impacts translate into macro-economic development and performance at the regional and national levels. We particularly focus on national-level impacts, including effects on food production and implications for rural and urban incomes and poverty reduction. In section 5, we summarize the main results and offer conclusions.

Groundnuts are predominantly cultivated in what is known as the Groundnut Basin of Senegal. Located in the west-central part of the country, this is Senegal's agricultural heartland and comprises the regions of Kaolack, Kaffrine, Fatick, Diourbel, Louga, and Tambacounda. Every year, groundnut crops occupy between 700,000 and 1000,000 hectares (ha) (ISRA-BAME 2020) and provide multiple benefits (Boote et al. 1998; Awal, Ikeda, and Itoh 2003). Mechanization is minimal, with animal traction employed for primary tillage and manual labor used for planting, weeding, and harvesting (ISRA-BAME 2020). Formal seed supply is limited by low production volumes and inefficient distribution networks, and most farmers rely on farmer-saved seed, which is often of inferior genetic and physiological quality (ISRA-BAME 2020).

Optimal sowing occurs within two weeks after the first effective rainfall, when soil moisture is adequate and temperatures exceed 18 degrees Celsius (°C) (Boote et al. 1998, 2018; Cox 1979). Fertilizer use remains low, mostly due to cost and availability issues, and, on average, farmers use below 26 kg/ha (ISRA-BAME 2020).

Modeling and Digital Twinning to Support Farming Decisions

A farm is a complex system where many processes occur simultaneously. It typically has several (or many) fields. Water is held in the soil of each field, transported vertically and horizontally, carrying with it dissolved nutrients. The soil also holds organic matter, which is transformed and mineralized through the action of earthworms, insects, and microorganisms. The soil is also influenced by farming activities: tillage uproots and buries weeds, breaks down soil aggregates, and redistributes soil constituents vertically; fertilization adds organic matter and other substances; and irrigation changes water content. A newly sown crop grows roots to explore the soil and access water and nutrients; it also grows leaves to capture light and photosynthesize, and, in time, it produces flowers that develop into harvestable produce. Much of the above is influenced by the weather: temperature, solar radiation, and precipitation are crucial. Other influences are also important; the prices of inputs (seeds, fertilizer, energy, labor) and outputs (harvestable produce) may determine the quantity of inputs used, and culture (tradition) or regulations may determine which crops are grown or at what time a particular crop is planted.

Farmers and researchers alike want to understand how a farm field "works". Farmers are interested in knowing, in a practical way, how best to manage a farm (or a field). By tradition, a farmer already has a good idea of how to manage a farm. Farming practices improve over time through small changes in farm management, keeping those that lead to better outcomes. Researchers are interested in understanding a farm scientifically. They aim to further their understanding by conducting designed experiments and deriving causal relationships between inputs, such as fertilizer, and outputs, such as physical and economic yield. In fact, despite their different aims, both farmers and researchers define a system and then use a model of this system to guide decision-making.

System analysis begins by defining the system to be studied. The studied system is always part of a larger system. Therefore, defining the studied system involves drawing a boundary around the part of reality that is of interest and explicitly identifying what is part of the system and what is not. For an in-depth description of system analysis, see Zeigler (1976) and Zeigler, Praehofer, and Kim (2000). Carreira, Amaral, and Vangheluwe (2020) provide a more recent description of system analysis.

Here, we will draw the boundary of the system of interest around the farm field, that is, around a piece of land on which a single crop is grown. The system will consist of the soil (to a depth which is somewhat greater than where crop roots can be expected to reach) and of the crop growing on the field. External influences on the system include the weather and the farmer's decisions about field operations.

A model is an abstraction of a system. It represents only some of the processes in the system and then represents them in a simplified form (a model that represents all processes in detail is a copy of the system rather than a model of it). Here, we consider crop growth models (CGMs), that is, models that represent the dynamics of soil water and nitrogen, as well as the growth and development of a crop. Many CGMs have been developed over the past 50 years; Asseng et al. (2013), for example, list 27 wheat models, and a similar number can be counted for potatoes (Fleisher et al. 2017; Raymundo et al. 2014). Well-known families of models include the World Food Studies (WOFOST) models (de Wit et al. 2019), the Decision Support System for Agrotechnology Transfer (DSSAT) models (Hoogenboom 2019), and the Agricultural Production Systems sIMulator (APSIM) (Keating et al. 2003).

There are several possible uses for CGMs. The first modelers aimed to test their understanding of the crop-soil system by expressing quantitatively what they knew about plants and determining whether the model could mimic observed behavior. This was fundamentally a scientific exercise in understanding the system, as evidenced by the focus of many early models on the fundamental leaf-level process of photosynthesis. Later, however, the big-leaf model was adopted (Goudriaan and Van Laar 1994; van Ittersum et al. 2003), making CGMs more suitable for studying the field-level processes of interest in this chapter.

Once reasonably well-functioning models of crop growth and development in the field were available, they were used to investigate crop management strategies. A strategy is a plan of action designed to achieve a long-term goal. A key strategic decision in cropping is choosing a planting date. In some environments, this decision aims to achieve a trade-off between planting too early, with the risk that the young crop dies if the start of the rainy season falters, and planting too late, which may cause crop ripening to take place in a part of the year that is too hot/cold/dry; in both cases, yield is ultimately reduced. A CGM is well-suited to quantifying the consequences of strategic choices; it can, for example, quantify the impact of weather variability on maize yields (White et al. 2025) or model potato yields in the different regions of Japan (Deguchi, Iwama, and Haverkort 2016).

CGMs can be used to foster a strategic understanding of the functioning of organic amendments. Well-known models that focus on soil organic matter dynamics include RothC (Coleman and Jenkinson 1996) and NDICEA (van der Burgt et al. 2006, 2007). Furthermore, Bostick et al. (2007) discuss the application of a soil organic matter model in Africa, and Bos et al. (2017) describe the use of a model to quantify the effect of organic amendments on subsequent crops in a rotation. To date, models of soil organic matter have not always fully taken into account the vertical distribution of organic matter in the soil, even though this distribution of soil organic matter can be highly relevant for shallow-rooting crops such as grassland, onions, potatoes, and groundnuts (Berghuijs et al. 2024).

CGMs are also used to support tactical decisions, that is, decisions that are made with a limited end in view. In field crop management, important tactical decisions relate to irrigation and fertilization, both of which can be applied several times during a growing season and typically aim to support crop growth over a time horizon ranging from days to a few weeks. Especially in dry environments with low soil nutrient supply, irrigation and mid-season artificial fertilizer application can have a strong positive effect on yield.

The literature contains examples of CGMs being used to inform tactical decisions. There are early examples of their use in cotton growing (McKinion et al. 1989; Hodges et al. 2018), with more recent research providing examples of where the fertilization and irrigation recommendations made by a CGM for a potato crop resulted in yields that were similar to when these decisions were made by an experienced farmer (Jansen, Davies, and Steenhuizen 2003). The breakdown rate and agronomic utility of organic amendments may be challenging to predict, and van Evert, De Visser, and Heinen (2006a) focus on a case where a CGM-based optimization in horticulture was given. Other studies describe cases where irrigation scheduling was supported by a model (Hsiao et al. 2009; Raes et al. 2009; Steduto et al. 2009).

As the literature cited above shows, a properly calibrated and initialized CGM can support farm management in at least three ways. These include:

- **Monitoring:** A CGM can identify which fields are experiencing water or nitrogen deficiencies (including not-observed variables).
- **Forecasting:** Using historic weather, local forecast weather, and regional/seasonal forecasts, a CGM can forecast whether water and/or nitrogen levels will be sufficient in the coming days.
- **Scenario exploration:** A CGM can evaluate alternative irrigation or fertilization schedules, particularly when resources (including economic) are limited.

In practice, despite careful calibration, model predictions tend to diverge over time from real-world conditions. This is expected because a CGM is an abstraction of reality and does not capture every aspect of a real farming system. Crop growth, for example, can be affected by salinity, soil hardpans, stagnant water due to irrigation, competition with weeds, and the effects of pests and diseases; however, these factors are rarely included in CGMs and are therefore not modeled as such. CGMs may also not be calibrated to local conditions; thus, crop parameters may not precisely reflect the local cultivar, and soil parameters may not exactly reflect the local soil. Unfortunately, when the model diverges from the reality on the farm, its results lose their value to the farmer. This is an important reason why the use of CGMs in practical farming is currently limited.

Digital twins of crop-soil systems

A digital twin is a dynamic model of a system that is kept synchronized with its real-world counterpart by making use of real-time data. In a process called data assimilation, the model uses real-world observations to make simulations match better with the modeled system.

Three main methods of data assimilation are distinguished: 1) forcing, where observations replace one or more state variables that would otherwise be simulated; 2) calibration, where model parameters are adjusted; and 3) filtering, where real-time observations and simulations are combined into a new, optimal estimation of the state of the system (see, for example, Jin et al. 2018; Jindo, Kozan, and De Wit 2023). The major drawback of forcing is that it implicitly assumes observations are error-free, whereas in reality they are subject to measurement errors. The major drawback to calibration is the risk of "getting it right for the wrong reason". One may, for example, adjust photosynthesis parameters to better reflect (observed) reduced growth, but that would be wrong if, in reality, a fungus is reducing the crop's leaf area. In this chapter, we are interested in the filtering method of data assimilation.

Filtering takes into account the uncertainty in both observations and simulation results and does not adjust parameter values. The most well-known filtering method is the Kalman filter (Grewal and Andrews 2010; Wallach et al. 2018). This filter cannot be used directly with a CGM; however, an alternative formulation, the ensemble Kalman filter (EnKF), can be used. We use an EnKF implementation that was originally proposed by de Wit and van Diepen (2007) and by de Wit, Duveiller, and Defourny (2012).

Two elements are critical for a digital twin. The first critical element is the model. Given the considerable effort expended to develop the complex process-based models introduced above and the fact that these models are generally able to simulate the crop-soil system adequately, it is logical that these models are the first choice for digital twin researchers. In section 2.2, we describe just such an effort. Other options, however, are possible. A digital twin explicitly accounts for the fact that it is not possible to model all relevant processes with a high level of realism, and it addresses this problem by using observations to adjust the model. The choice of which model to use in a digital twin depends, in part, on: 1) how far ahead in time the digital twin must forecast, and 2) how frequently observations are made. Where a decision made today has a future impact — for example, on crop yield two months hence — it is often thought that complex CGMs are superior to simpler statistical models. For shorter forecasting time horizons, however, simpler models may be just as effective. Where only infrequent observations are made between the sowing and forecasting dates, one must rely more on models, and the quality requirements for those models will be higher. With frequent observations available for adjusting model states, sufficient precision may be provided by a simple process-based model (van Evert, De Visser, and Heinen 2006b; Zhao et al. 2019) or even a statistical model (e.g., a machine learning model).

The second critical element is real-time data for filtering. This data must be available at high frequency, with low latency, at scale, and, of course, be of high quality. Data sources that can be used for digital twins include optical and radar satellites, unmanned aerial vehicle (UAV) imagery, and installed soil moisture sensors (Table 16.1). Soil scanners such as Veris U3 (Veris Technologies, Salina, KS, United States), EM38-MK2 (Geonics Limited, Mississauga, Ontario, Canada), and DUALEM-21 (Dualem Inc., Milton, Ontario, Canada) provide useful information for model parameterization, but the measurements are made on bare soil; they thus cannot be used for data assimilation during the growing season.

TABLE 16.1—SOURCES OF DATA AND A QUALITATIVE ASSESSMENT OF CHARACTERISTICS RELEVANT FOR DIGITAL TWINNING

Source	Observation	Frequency	Latency	Scalability	Usefulness for DT
Optical satellite	Biomass	Days/weeks	Day	Yes	Good
	N uptake	Days/weeks	Day	Yes	Good
Radar satellite	Biomass	Days/weeks	Day	Yes	Indicative
	Soil water	Day	Day	Yes	Indicative
UAV imagery	Biomass	Day	Day	Yes/no	Good
	N uptake	Day	Day	Yes/no	Good
	Water stress	Day	Day	Yes/no	Good
Crop sensors	Biomass	Day	Day	Yes/no	Good
	N uptake				
Soil moisture sensors	Soil water	Minute/hour	Minute/hour	No	Very good
Soil scanner	Soil properties	Year	-	Yes/no	Indicative

Note: DT = digital twin; UAV = unmanned aerial vehicle; N = nitrogen.

Applying digital twins to farming in Europe: The case of potatoes in the Netherlands

We have constructed a digital twin for potatoes in the Netherlands (van Evert et al. 2024a, 2024b) that uses the Tipstar potato model (Jansen 2008; Jansen, Davies, and Steenhuizen 2003), which is described in detail by van Oort et al. (2024). Tipstar can simulate any of the three production scenarios that are commonly recognized in crop-soil modeling (van Ittersum et al. 2003), namely potential production (Yp), water-limited production (Yw), and water-and-nitrogen–limited production (Yw,n). In the potential production scenario, crop growth and development are determined solely by crop (cultivar) traits and the weather, which obviously depends on location and planting date. In the water-limited scenario, crop growth may be reduced due to water stress. Water dynamics in the soil are modeled with a tipping bucket model. Water-and-nitrogen–limited production is the same as water-limited, but with additional simulation of growth reduction if not enough nitrogen (N) is available. Nitrogen dynamics in the soil are modeled using a soil organic matter model originally described by Verberne et al. (1990) and Jongschaap (1996).

Access to farm data is critical to the success of a digital twin and to the usefulness of farm-related apps in general. At the same time, in many cases, farm data is not well organized. The EU has recognized this, and a Common European Agricultural Data Space (CEADS) is currently being implemented. Architecturally, CEADS is a federated system where the nodes are called data sharing initiatives (DSIs).

The potato DT retrieves all input data from a DSI called FarmMaps (Been et al. 2023), a cloud-based data and service platform for precision agriculture. FarmMaps provides basic apps and services such as weather, soils, and satellite data, as well as more specific farm-related applications. For the Netherlands, FarmMaps provides soil physical data from the Dutch national database (Heinen et al. 2021). For the rest of the world, FarmMaps provides soil physical data from

SoilGrids (ISRIC–World Soil Information 2025; Hengl et al. 2015), with additional soil physical parameters calculated using the methods described by Tóth et al. (2015). Weather data (current, historic, and 14-day forecasts) are obtained from a commercial provider, while satellite imagery is obtained from Sentinel Hub and other providers. Drone imagery, if available, can be uploaded by users and then linked to the relevant crop fields. Field operations can be recorded directly in FarmMaps or retrieved from a commercial Farm Management Information System (FMIS) if the farmer uses one.

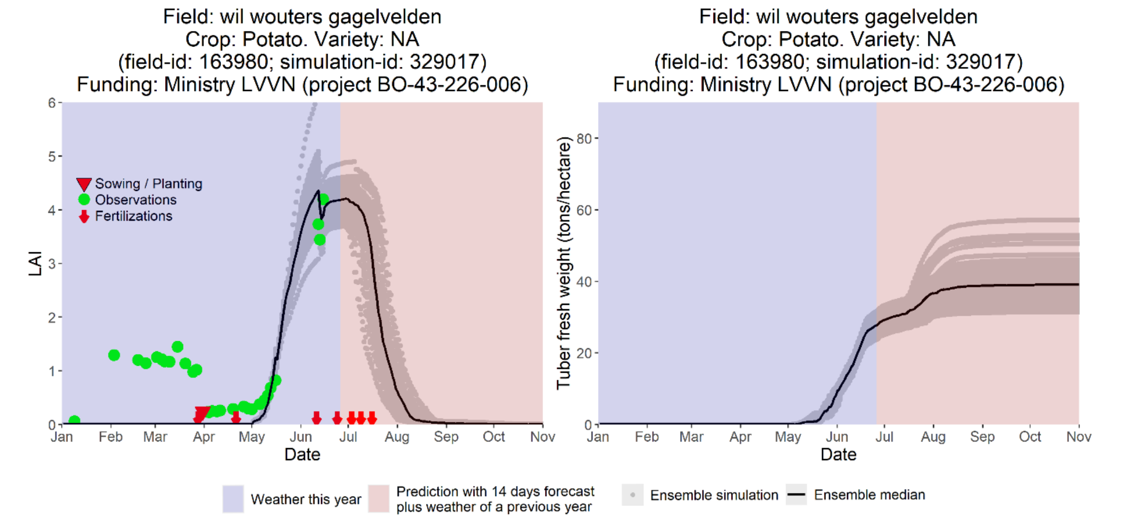
The potato digital twin has been implemented at Van den Borne Potatoes, a commercial potato farm that plants approximately 500 hectares (ha) of potatoes each year. Van den Borne is located in the south of the Netherlands on shallow, coarse, sandy soil. There is a relatively large variation in texture, soil organic matter, and profile depth within and between fields, which poses management challenges.

Since about 2010, Van den Borne Potatoes has been proactive in documenting their operations, including farm management, yields, soil analyses, and in-season crop growth measurements, which has been captured in several research reports (Mulders et al. 2021, 2024; van Evert et al. 2019; Yan, Reidsma, and Kroes 2015).

Van den Borne uses a commercial FMIS to record field operations, including tillage, sowing, irrigation, fertilization, and harvesting. The FMIS is cloud-based, which makes it relatively straightforward to retrieve farm management data in real time.

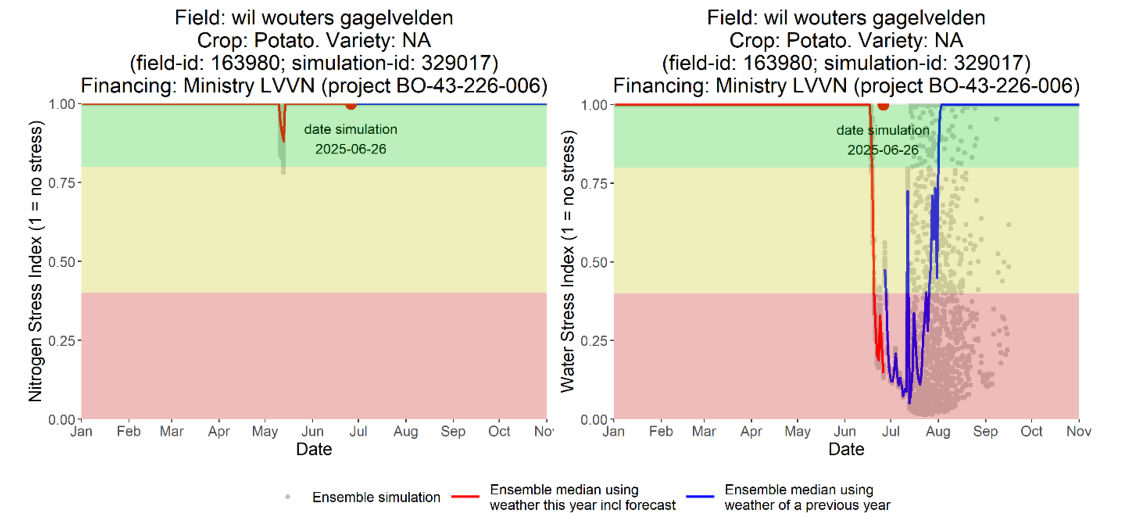
Representative results from the digital twin are shown in Figures 16.1 and 16.2. These are results for a three-hectare field where potatoes were grown in 2025. Figure 16.1 shows simulated leaf area index (LAI) and fresh tuber weight, as well as a LAI estimate derived from satellite remote sensing. Each time an observation becomes

FIGURE 16.1—OUTPUT FROM THE DIGITAL TWIN, VAN DEN BORNE POTATOES, JULY 11, 2025



Notes: The left panel shows simulated leaf area index (LAI) as a function of time; the right panel shows simulated tuber weight. Observed weather was used for the period from the beginning of the year to the current date (indicated by the purple background); forecast weather was used for the first two weeks after the current date; weather from previous years was used for the remainder of the year (pink background); the digital twin consisted of 30 different simulation curves, indicated by grey dots, each one made with a slightly different set of parameters to represent the uncertainty in the prediction; the solid black line is the median of the curves and represents the best estimate of the state of the system; the green symbols indicate LAI estimated from satellite imagery.

FIGURE 16.2—OUTPUT FROM THE DIGITAL TWIN, VAN DEN BORNE POTATOES, JULY 11, 2025



Notes: The left panel shows the sufficiency of water, where 1 means there is sufficient water for the crop to grow, and numbers smaller than 1 mean that growth is limited by availability of water; the right panel shows the sufficiency of nitrogen, where 1 = sufficient N.

available, it is used to adjust the state of the model, taking into account the uncertainty of the observation as well as the uncertainty of the simulation.

From information to recommendation

The digital twin provides detailed, accurate, and up-to-date information about the current state of the system. It also provides a forecast of the future state of the system. The quality of the forecast depends heavily on the quality of the weather forecast that is used. Fortunately, weather forecasts for one or two weeks are quite reliable in many parts of the world and are becoming even more reliable over time through the use of AI (see Price et al. 2025); thus the information that is provided in Figure 16.2 (that the crop will experience a severe shortage of water in the next week) is a serious indication that irrigation will be necessary to avoid impeded crop growth. This information is useful to a farmer, especially one such as Van den Borne, who struggles to monitor all 200 potato fields.

The above, however, is not yet a recommendation for action. The difference between information and recommendation can be illustrated through a consideration of the interplay between water and nitrogen at the Van den Borne farm. The farm is located on shallow sandy soil with limited water-holding capacity, and in many years, irrigation will be necessary for a large part of the growing season. Van den Borne uses mobile sprinkler irrigation systems that are moved from one field to another, as the farm does not have enough sprinklers to fully irrigate all fields simultaneously. In addition, during dry years, the local water authority limits the amount of water available for irrigation. There are thus years when, even with the best efforts, the potatoes will grow with a suboptimal water supply.

Potato is a voracious user of nitrogen due to its inefficient root system and the large amount of N accumulated in the tubers. Nitrogen supplied in excess of what the crop needs will remain in the soil after harvest and contribute to nitrate pollution of the groundwater during the winter, especially in the case of shallow sandy soils. Fortunately, N leaching can be reduced by splitting the application of N fertilizer (van Evert et al. 2012; Vos 1999). Following this practice, Van den Borne applies a limited amount of fertilizer at planting and applies sidedress

FIGURE 16.3—ILLUSTRATION OF THE STEPS IN TURNING INFORMATION INTO A RECOMMENDATION (SEE MAIN TEXT FOR EXPLANATION)

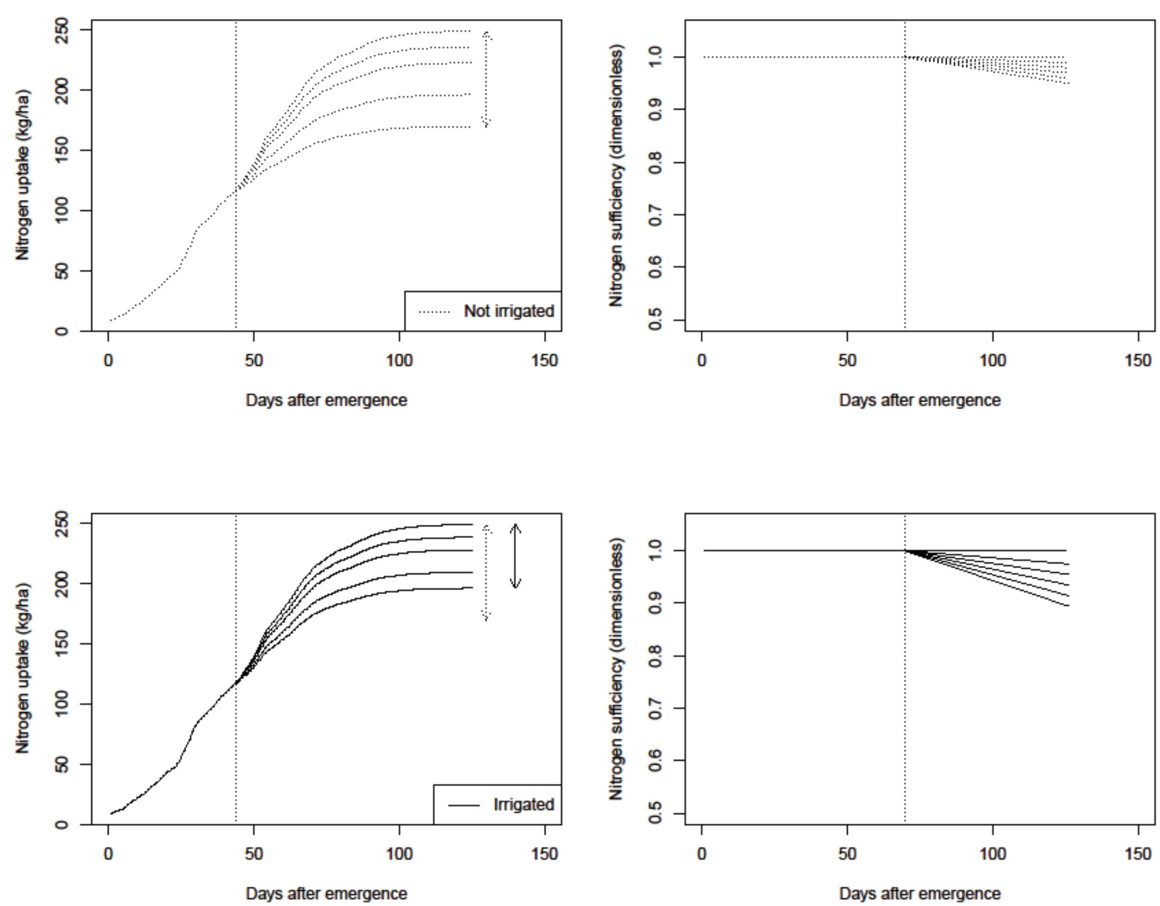


FIGURE 16.4—EXPECTED POTATO YIELDS IN TONS PER HECTARE (T/HA) FOR SEVERAL FIELDS ON THE VAN DEN BORNE FARM, IN FOUR SIMULATED SCENARIOS (SEE MAIN TEXT FOR FULL EXPLANATION)

	Potato yield (t/ha) in four scenarios, as forecast on August 14			
	Zero extra irrigation	Zero extra irrigation	Irrigation if needed	Irrigation if needed
Crop field (number and name)	Zero extra fertilizer	+ extra fertilizer	Zero extra fertilizer	+ extra fertilizer
163226. jacob pielis spie	27	27	30	30
163227. peerke snip peel	54	54	64	65
163536. anny cuypers achter stal	38	38	38	38
163537. anny cuypers berendonk	32	32	35	38
163540. bart nijs achter paul stessens	37	37	44	47
163541. bart nijs spie schillebeeksbos	33	33	33	36
163542. bart nijs wilgeboom	39	39	46	47
163543. bart rommens geel ten aard	41	41	41	45
163544. bart rommens geel ten aard klein	41	41	42	44
163545. bart rommens nelis kastelseweg	41	41	47	50
163546. bart rummens walterstuk	20	20	20	21
163547. bart tormans jos cuypers voor	33	33	36	37
163548. bart tormans loopje	31	31	31	32
163549. ben keizerstraat	21	21	26	27
163550. ben labeets fernand	20	20	20	22

Notes: In Scenarios 1 and 2, no irrigation was applied; in Scenarios 3 and 4, irrigation was applied as needed; in Scenarios 1 and 3, no extra fertilizer was applied; in Scenarios 2 and 4, an additional fertilizer application was made.

nitrogen as needed, at two-week intervals. The question thus arises: how much N does the crop need, given that it is suboptimally supplied with water? We argue that this question can be answered with the help of the DT.

Figure 16.3 shows a simplified representation of the output of the potato digital twin. The top left panel shows a five-member ensemble of simulations. The current time is indicated by the vertical dashed line. It is assumed that at this point in time, everything is perfectly known; therefore, the curves of the five members of the ensemble coincide. For the period from the current time to the end of the season, a different year of past weather data is used for each ensemble member. In a year with favorable weather (lots of sunshine, rain whenever it is needed), growth will be good, and the highest growth curve will be the result. In a year with unfavorable weather (cold and dark, little or no rain), growth will be poor, as represented by the lowest curve. The remaining three curves are the result of intermediate weather.

The top right panel of Figure 16.3 shows the N sufficiency for each of the ensemble members, given a certain level of fertilizer application. If the weather (and thus growth) is poor, the amount of N is sufficient (horizontal line at 1), but if the weather (and growth) is increasingly better, the amount of N that was sufficient for a poorly growing crop is increasingly insufficient; this is indicated by the curves that dip below the horizontal line at 1.

The bottom half of Figure 16.3 shows what happens when the farmer uses irrigation to support the crop during dry periods. In the left panel, the uppermost curve does not change—here the crop is growing at the potential rate (not limited by water); the lower curves, however, shift upwards. The distribution of possible outcomes (yields) changes: the average increases, the range decreases. But higher yields must be supported by a greater amount of N. The bottom-right panel shows that higher yields lead to greater N insufficiency.

This information can be used to make a recommendation by running the simulation with different fertilizer amounts; the fertilizer amount that prevents an unacceptable N insufficiency can then be recommended. As an illustration, Figure 16.4 presents mocked-up potato yields for several fields on the Van den Borne farm under four hypothetical scenarios. The scenarios differ with regard to whether extra irrigation and extra fertilizer were applied after August 14, giving rise to the following observations:

- **No extra irrigation, extra N:** If, from August 14 onwards, extra nitrogen was applied without extra irrigation, the impact on yield would be zero; there is thus no need for extra fertilizer application.
- **Extra irrigation, no extra N:** If, from August onwards, extra irrigation was applied without extra fertilizer, some yield gain would still be possible. Notably, this forecast is made in the later part of the growing season when the crop is already senescing; therefore, yield gains are relatively small. One could imagine a larger scope for yield increase earlier in the growing season if irrigation is applied throughout.
- **Extra irrigation, extra N:** In a few fields, "irrigation + fertilizer" shows slightly higher yield forecasts than solely "irrigation".

As a final step, these scenarios could be used in a cost–benefit analysis using three economic parameters: market gate price, cost of irrigation, and cost of fertilizer. A net profit can be made on a particular field if the yield gain * market gate price > cost of extra irrigation. Even if models indicate that a yield gain is possible, one may still decide not to irrigate if the cost of irrigation exceeds the expected increase in gross profit.

A Digital Twin for Africa: the Case of Groundnuts in Senegal

The agronomy of groundnuts (*Arachis hypogaea* L.) in Senegal

Groundnut (*Arachis hypogaea* L.) is an important crop in Senegal, but the national average yield of 1 to 1.2 t ha^{-1} is well below the biophysical potential of 3.5 to 5 t ha^{-1} that is achievable under ideal agronomic and climatic conditions (Boote et al. 1998). This section first describes some of the reasons for this low productivity, then explores modeling and digital twinning as a technology for improving groundnut management. In this section, we examine the agronomic and economic environment of groundnuts in Senegal, including the factors contributing to low productivity and pathways to improved yields. Based on the analysis in this section, in section 4, we assess the potential impact on farming and the broader economy that could be achieved with a technology such as digital twinning.

Strategic role of groundnut in Senegalese agroecosystems

Groundnut is one of Senegal's most vital crops, not only for its economic value but also for its pivotal role in the agroecological sustainability of rural farming systems. It is cultivated predominantly in the Groundnut Basin, which comprises the Kaolack, Kaffrine, Fatick, Diourbel, Louga, and Tambacounda regions. Every year, it occupies between 700,000 and 1000,000 ha (ISRA-BAME 2020).

The groundnut crop provides multiple benefits. It enhances soil fertility through symbiotic nitrogen fixation, it supports household food and income security, and it underpins livelihoods in a fragile rainfed agricultural system.

As mentioned above, however, despite its long-standing cultivation and strategic relevance, groundnut productivity remains below its biophysical and economic potential. The persistence of this yield gap is rooted in a combination of factors, including suboptimal input use, low varietal adoption, climate variability, and institutional inefficiencies. The urgency to address these limitations has never been greater, especially in the face of increasing climate variability.

Biophysical and socioeconomic context of groundnut production

Climatic and soil conditions

Groundnut production in Senegal is concentrated in the Sudano-Sahelian agro-ecological zone, which receives between 400 and 900 mm of annual rainfall over a 3- to 4-month rainy season (June to September). Soils are typically sandy loam to sandy in texture, with low organic matter, poor cation exchange capacity, and high susceptibility to erosion and crusting (Awal, Ikeda, and Itoh 2003). These characteristics are particularly significant for groundnut, given its geocarpic nature: pegs formed from fertilized flowers must successfully penetrate the topsoil to initiate pod development.

Soil crusting and compaction, which hinder peg penetration, are common in these sandy soils; furthermore, air temperatures above 36°C during flowering, and soil temperatures exceeding 34°C during pegging, are known to induce sterility, reduce fertilization success, and impair pod development (Hamidou, Halilou, and Vadez 2012). Aligning agronomic practices with climatic conditions is thus critical for yield stabilization.

Farm structures and cropping systems

Senegalese groundnut farming is characterized by smallholder systems with landholdings ranging from two to five hectares. Production is integrated with other staple crops, such as millet, cowpea, and sorghum, which are typically managed under low-input conditions. Mechanization is minimal, with animal traction employed for primary tillage and manual labor used for planting, weeding, and harvesting (ISRA-BAME 2020). Access to credit, input supply chains, and extension services remains limited and uneven across regions, leading to disparities in productivity and resilience.

Seed systems and varietal use

Varietal innovation has yielded several improved cultivars, including Fleur 11, Sunu Gaalé, 73-33, and 55-437, developed by ISRA and its partners. These varieties combine higher yield potential with resistance to common pests and diseases. Adoption remains constrained, however, due to weak seed systems; low production volumes and inefficient distribution networks also limit formal seed supply. Most farmers rely on farmer-saved seed, which is often of inferior genetic and physiological quality (ISRA-BAME 2020).

Crop management practices

Land preparation and sowing practices

Proper land preparation is essential for maximizing germination and peg penetration. Most farmers employ animal-drawn plows, occasionally complemented by harrowing to reduce surface crusts. Optimal sowing occurs within two weeks after the first effective rainfall, when soil moisture is adequate and temperatures exceed 18°C (Cox 1979). Planting outside this window increases vulnerability to terminal drought and heat stress.

Field experiments show that early sowing, especially in late May or early June, can significantly enhance productivity by aligning reproductive stages with favorable environmental conditions (Boote, Jones, and Hoogenboom 2018). Delayed planting, by contrast, increases exposure to late-season heat waves that impair reproductive processes.

Nutrient management

Although groundnut can meet its nitrogen needs through biological fixation, it is highly responsive to phosphorus (P), calcium (Ca), and boron (B). Phosphorus improves root development and nodulation and should be applied at rates of 20–40 kg P2O5/ha at planting. Calcium, typically administered as gypsum at 1,000 to 1,500 kg/ha, is crucial during early flowering for pod and kernel formation (Boote et al. 1998). Boron, applied at 0.5 to 1 kg/ha, prevents hollow heart and enhances seed quality.

Largely due to cost and availability contraints, fertilizer use remains low, averaging less than 26 kg of fertilizer product per hectare (ISRA-BAME 2020). Farmers frequently apply farmyard manure or compost, although these are often insufficient in quantity and poorly integrated into the overall nutrient strategy.

Water management

Drought is a major yield-limiting factor. Water stress during flowering and pegging stages can reduce yields by more than 50 percent (Hamidou, Halilou, and Vadez 2012). Although irrigation is rare, moisture conservation techniques such as mulching, tied ridges, and conservation tillage could help buffer against dry spells. The use of weather and soil moisture forecasts is emerging as a critical tool for optimizing planting dates and managing water stress.

Pest and disease management

Groundnut is susceptible to a variety of biotic stresses, including fungal diseases (early and late leaf spots, rust), viruses (rosette disease), and insect pests (aphids, thrips). Pathogen pressure is particularly high during humid conditions or under continuous groundnut cultivation. Resistant varieties and crop rotation offer cost-effective control strategies, supplemented by fungicides where economically viable; however, adoption of integrated pest management remains limited due to weak extension services.

Production performance and economic viability

Despite strategic investments, groundnut productivity remains low. With labor comprising up to 60 percent of total production costs, yield variability significantly impacts profitability. Financial viability is determined mainly by yield levels: returns are positive above 1.5 t/ha but become marginal or negative below 1 t/ha.

Value chain constraints include price volatility, limited aggregation mechanisms, and lack of access to quality inputs. Strengthening producer organizations, improving access to credit, and developing rural infrastructure are essential to improving overall economic returns from groundnut farming.

Strategic pathways for sustainable intensification

The following strategies offer a roadmap for enhancing productivity and resilience in Senegalese groundnut systems:

- **Genetic improvement:** Scale-up of stress-tolerant, high-yielding varieties via strengthened formal and community seed systems
- **Soil fertility management:** Promotion of integrated soil fertility management that is tailored to local soil conditions
- Water and climate risk management: Investment in localized weather services and climate-smart practices

- **Digital decision support:** Integration into extension platforms of remote sensing and crop simulation models such as CROPGRO-Peanut
- **Market linkages:** Establishment of aggregation centers and digital market platforms to improve price realization and reduce transaction costs

If adopted at scale, these interventions could substantially close the yield gap, improve profitability, and build resilience in Senegal's groundnut sector.

Digital-twin–based agronomic scenarios for groundnut production

As described above, groundnut production in Senegal is constrained by weather variability, nutrient deficiencies, and timing mismatches between crop phenology and environmental conditions. Digital twin (DT) technologies, which combine real-time weather, soil, and crop data with predictive modeling, offer a transformative pathway for addressing these challenges. This section details four agronomic scenarios built from field realities in Senegal. For each scenario, we present both agronomic implications and economic outcomes, notably the effects on gross margins derived from farmer-level production data, and the role that a model or a digital twin could play.

Scenario 1: Early onset of rains and optimized sowing dates

This scenario reflects conditions where early rainfall allows timely sowing, enabling synchronization between crop phenology and optimal climatic windows. A model-based application can simulate sowing advisories using seasonal forecasts and soil temperature profiles, so as to reduce exposure to terminal heat stress. Important factors here are: 1) predicting the onset of the wet season (Sultan and Janicot 2003), and 2) overcoming socioeconomic barriers to ensure timely soil preparation and timely availability of credits, seed and fertilizer at the start of the growing period (for rice in Senegal, suboptimal late sowing is often attributed to these factors; see, for example, Brosseau et al. 2021; Tanaka, Diagne, and Saito 2015).

Agronomic impact: Empirical evidence indicates that sowing two to four weeks earlier than traditional dates can increase yields by 20 to 30 percent (Boote et al. 2018; Cox 1979). This benefit stems from improved flowering conditions (28 to 30°C) and reduced pod abortion.

Scenario 2: Mid-season drought during flowering and pegging

This scenario simulates a dry spell during the pegging phase, one of the most drought-sensitive stages for groundnut. A digital twin can help farmers respond optimally by advising timely light irrigation or mulching to preserve surface soil moisture. Not all CGMs are capable of simulating the effect of mulch on soil temperature; therefore, the model selected as the basis for the digital twin may need to be extended to account for this effect.

Agronomic impact: Drought during pegging can reduce yields by 40 to 60 percent (Hamidou et al. 2012); however, soil moisture conservation practices can recover up to 25 percent of lost yield (Awal, Ikeda, and Itoh 2003). DTs can monitor soil moisture and provide localized alerts for action Scenario 3: Late-season heat stress during pod filling

Late-season heat waves frequently occur during the pod-filling phase, reducing kernel mass and overall productivity. DT systems can forecast high-temperature periods and support decisions to adjust sowing dates early in the season to avoid exposure.

Agronomic impact: Pod filling is optimal at 24 to 26°C. Temperatures exceeding 34°C sharply reduce kernel weight and seed formation (Awal, Ikeda, and Itoh 2003, Boote et al. 2018). Model simulations show that adjusting sowing dates to avoid late-season heat can prevent yield losses of 15 to 20 percent.

Scenario 4: Low inputs and degraded soil (no DT intervention)

This scenario represents the status quo among smallholder farmers with limited access to improved seeds, fertilizer, or agronomic knowledge. It serves as the control benchmark.

Agronomic impact: Yields are often constrained below 1 t/ha due to calcium and boron deficiencies, water stress, and lack of varietal innovation (Boote et al. 1998; Laza et al. 2021). Fertilizer use is often 30 to 50 percent below recommended rates, and labor is underutilized or misaligned with crop needs.

Realizing a digital twin for groundnuts

We conclude this section with some thoughts on what would be needed to realize a digital twin for groundnuts in Senegal.

Building a digital twin

It has been mentioned that for a digital twin, one needs:

- A model, calibrated and tested for local conditions
- Crop management data: sowing dates, cultivar data, irrigation and fertilizer dates and amounts
- Local soil data
- Local weather data
- Real-time observations on simulated model variables, such as leaf area index or soil moisture content

Fortunately, a well-established groundnut model, CROPGRO, is available (Boote, Jones, and Hoogenboom 2018). There are many scientific papers that describe the workings and applications of this model. Like many other CGMs, however, CROPGRO is a complex model and, for a digital twin, a less complex model such as SIMPLE may be just as useful (Zhao et al. 2019).

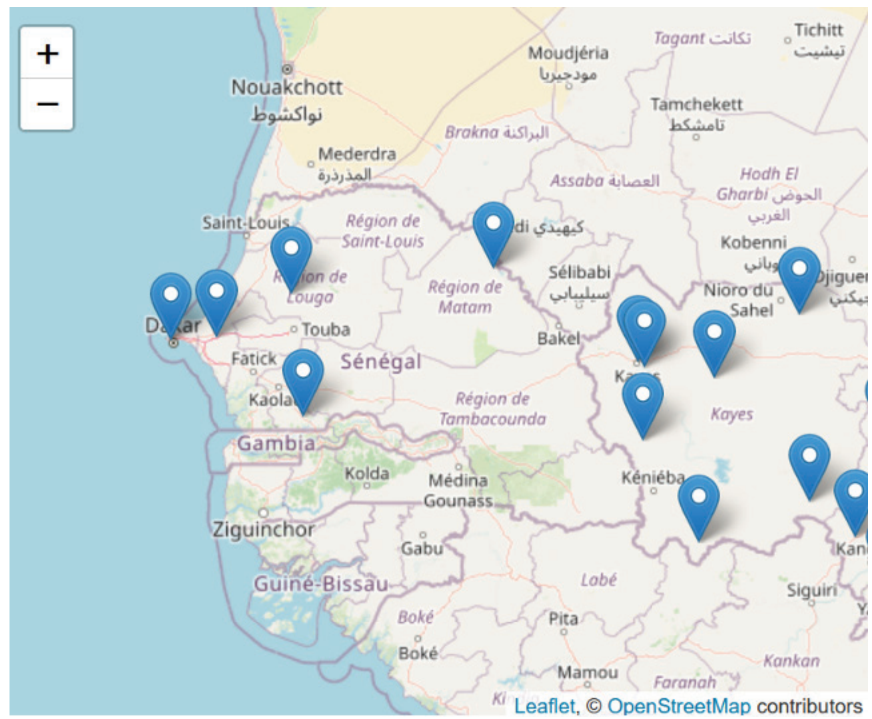
Local soil data can be obtained from national soil maps or from public data sources such as SoilGrids (Hengl et al. 2015), complemented by derived soil physical parameters (Tóth et al. 2015). Weather data is, in the first instance, the responsibility of Senegal's *Agence Nationale de l'Aviation Civile et de la Météorologie* (ANACIM); in addition, the Trans-African Hydro-Meteorological Observatory (TAHMO) (https://tahmo.org/) is developing a network of weather stations across Africa, including in Senegal. This network is not yet complete; however, given that they work with inexpensive yet robust sensors, it could be quickly expanded in specific regions if needed for digital twin applications (Figure 16.5 provides an overview of current stations).

Satellite imagery from Sentinel-2 provides real-time observational data on crop leaf area and above-ground biomass. Soil moisture content in the topmost soil layer can be estimated from L-band radar imagery. An important reason digital twins did not previously use satellite imagery was its low temporal frequency and coarse pixel size, which were not well suited to small crop fields in spatially heterogeneous croplands. When this is an issue, drone (UAV) data can be used, but it is more expensive, and the area that can be monitored is far smaller than with satellite imagery.

A scalable digital twin

If at some point in the future a digital twin for groundnuts is realized, tested, and deemed useful to farmers, large-scale operational access to the digital twin will need to be organized. This would require an Information and Communications Technology (ICT) platform to host the data, run the model, and provide a user interface. It would also require a revenue model to defray the costs of running such a platform. The revenue model could rely on subscription fees charged to farmers, or it could be supported by a subsidy; it could also draw on a mix of

FIGURE 16.5—MAP SHOWING THE LOCATION OF TRANS-AFRICAN HYDRO-METEOROLOGICAL OBSERVATORY (TAHMO) WEATHER STATIONS IN SENEGAL AND MALI, JULY 22, 2025



Source: TAHMO Weather Station Data (https://tahmo.org/climate-data/).

these (and other) options. It would require a training program to help farmers and farm advisors make use of the new system, as well as a support program to address day-to-day issues. Sustaining public or private investment in building a digital twin and keeping a scalable version up and running will only be sustainable if farmers (or other users) actually use the tools. They will only do so if they feel it helps them make better decisions.

Modeling Potential Impacts of Digital Twins on Farming and Induced Inclusive Economic Growth in Senegal

In this section, we conduct a comprehensive economic analysis of the potential impacts of implementing digital twin technologies in Senegal. We take it as a basic assumption that DT technology is implemented as a public service by a regional state agency; that is, we assume that in Senegal, unlike in Europe, DT technology is applied locally to provide individual farmers with forecasts of relevant biophysical parameters and with management recommendations that are tailored to single plots on individual farms.

Our analysis begins with a micro analysis of potential productivity gains at the farm level. We then conduct a corresponding macro analysis to see how productivity gains at the farm level diffuse through the overall economic system. For the micro analysis, we apply a Data Envelopment Analysis (DEA) to identify the regional potential for unlocking productivity gains at the farm level; at the same time, we also apply a regionalized Micro-Macro Equilibrium Model to identify how the farm-level productivity gains induced by the introduction of DT technology translate into economy-wide shocks and into induced responses at the household level and the level of the agriculture and non-agriculture sector. The regional micro-macro modeling approach allows for an assessment of the ultimate impact of DT technology shocks on relevant Sustainable Development Goals (SDGs), namely, poverty and per capita income at the regional and national levels, respectively.

Based on the DEA analysis outlined in section 4.1, we could identify great potential for increased technical efficiency at the farm level for groundnut, but also for other crops such as millet and maize. These significant potential gains in agricultural productivity align with the relevant literature and represent a promising pathway to promoting inclusive, sustainable growth in Africa.

Transforming the identified potentials of digital twin technology to increase productivity at the farm level, however, implies an analysis of economy-wide responses to micro-level technology shocks (this analysis will be done in section 4.2). Here, we first explain our methodological approach. In addition to describing the applied quasi-dynamic CGE model, we also explain the intervention logic of implementing a digital twin technology that supports individual farm decisions in Senegal.

Economic impact at the farm level

To empirically identify potential productivity gains achievable with DT technology at the farm level, we applied a DEA analysis using micro-farm data collected in the *Projet d'Appui aux Politiques Agricole*s (Agricultural Policy Support Project, or PAPA) conducted from 2015 to 2018 in Senegal. Below, we first briefly describe our applied methodological approach, including the data we used; we then describe the main results.

Data Envelopment Analysis model

To empirically identify potential productivity gains induced by digital twin technology, we conducted a DEA analysis. DEA is a non-parametric methodology used to assess the relative efficiency of decision-making units (DMUs) such as farms, firms, or regions, based on multiple inputs and outputs. Originally introduced by Charnes, Cooper, and Rhodes (1978), DEA compares each unit to a constructed "efficiency frontier" that represents the best observed performance in the dataset. Units on the frontier are considered efficient, while those below it are considered inefficient and receive a score between 0 and 1. DEA is particularly valuable in agricultural applications because it does not require prior assumptions about production functions. It accommodates multiple heterogeneous inputs, such as land, labor, seed, and fertilizer, and multiple outputs, such as yield and income. This makes it well-suited to evaluating farm-level performance in real-world conditions. Depending on policy goals, DEA can be modeled in two orientations: input-oriented (minimizing inputs for a given output) or output-oriented (maximizing output with given inputs). DEA has been widely applied in African agricultural research to identify best practices, quantify productivity gaps, and inform policy for extension, training, and technology diffusion.

Data source and survey design

This report draws on data from the 2017 national agricultural production survey in Senegal, known as PAPA 2017. The survey was led by the Directorate of Analysis, Forecasting and Agricultural Statistics (DAPSA) using the harmonized methodology for West Africa, developed by the *Comité Permanent Inter-États de Lutte contre la Sécheresse* dans le Sahel (Permanent Inter-State Committee for Drought Control in the Sahel, or CILSS). The focus was on rainfed crop systems, which dominate Senegalese agriculture. A two-stage stratified sampling design was used. The primary units were enumeration areas from the 2013 *Recensement Général de la Population, de l'Habitat, de l'Agriculture et de l'Élevage du Sénégal* (General Population, Housing, Agriculture, and Livestock Census of Senegal, or RGPHAE); secondary units were agricultural households. The survey sampled 4,533 rainfed farming households from a national frame of over 458,000. Data were collected in April and May 2017 across 42 agricultural departments (excluding Dakar, Pikine, and Guédiawaye). Survey modules covered crop production, input use, labor, sales, and household characteristics. The result is a nationally representative dataset of crop farms; this enables analysis by farm size, input levels, and regional distribution, and supports evidence-based agricultural policy and planning.

The regional breakdown of the PAPA farm survey corresponds to 45 departments, which can be aggregated into 14 regions (Figure 16.6).

FIGURE 16.6—ADMINISTRATIVE UNITS IN SENEGAL

Source: Wikimedia Commons (https://commons.wikimedia.org/w/index.php?curid=7820529).

To assess potential productivity gains, we conducted a DEA analysis for each crop in each of Senegal's 14 regions. As a central output of our DEA analysis, we derived the input and output efficiency measures for all individual farms in each region and for each crop. Also, based on identified input- and output-oriented efficiency measures, we were able to calculate the corresponding yield gains achievable by each individual farm, assuming it was outcome-efficient.

Let $a_{(ij)}$ denote the output efficiency measure of farm i, and $Y_{(ij)}$ the yield realized by farm i for crop j. The additional yield that a farm can realize with the same input is thus:

$$\Delta Y_{ij} = (a_{ij} - 1) \cdot Y_{ij} \tag{1}$$

Similarly, with input efficiency $0 < b_{ij} < 1$, the same output Y_{ij} can be achieved with an input reduction of:

$$\Delta x_{ij} = (1 - b_{ij}) \cdot x_j \tag{2}$$

Given revenue $Rij = Yij \cdot Pij$ and cost $Cij = \Sigma\, Q_{ijk} \cdot X_{ijk}$, the increase in gross margin G can be expressed as:

$$\Delta G_{ij} = (a_{ij} - 1) \cdot R_{ij} \tag{3}$$

$$\Delta G_{ij} / G_{ij} = (a_{ij} - 1) / (1 - (C_{ij} / R_{ij}))$$

$$\Delta G_{ij} = (1 - b_{ij}) \cdot C_{ij}$$

$$\Delta G_{ij} / G_{ij} = (1 - b_{ij}) / ((R_{ij} / C_{ij}) - 1)$$

This implies that the absolute increase in gross margin results as a multiple $(a_{ij} - 1)$ of revenues, depending on output efficiency. Similarly, the gain from input efficiency is a multiple of costs. Less-efficient farms (higher a_{ij} or lower b_{ij}) show higher potential gains, though their total gross margins may remain low. Relative gains depend on the cost–revenue ratio; a higher share of cost in revenue leads to a higher relative gain in gross margin.

Results

Regional farm structures and production patterns

In this section, we report the calculated input and output efficiencies derived from our DEA analysis. As we conducted a regional DEA analysis for each crop separately, we obtained a large number of efficiency measures. The pattern of technical inefficiency we observed, however, was relatively similar across different crops; we therefore report detailed results only for groundnut

To facilitate better interpretation of estimated regional technical inefficiency measures, we will first report regional farm structures for the regions with PAPA survey data.

In Table 16.2, we see that the farm structure in the groundnut sector is characterized by medium- and large-sized farms, which together account for over 84 percent of groundnut producers, and that the highest yields are found among very small farms. This counterintuitive pattern suggests more efficient, intensive practices or better soil on smaller plots. Larger farms apply much more seed and fertilizer but see lower returns, indicating input inefficiency. These results support the case for tailored scale-sensitive support to improve productivity and equity across producer categories.

Table 16.2 reports input use by farm size classes. This breakdown underscores the inverse relationship between farm size and yield: despite having the smallest cultivated area, very small farms achieve the highest yields. Larger farms, meanwhile, use significantly more inputs without enjoying corresponding gains in productivity. This points to inefficiencies at scale and underscores the importance of extension services and training on input optimization. The steep increase in fertilizer and seed use on large farms also raises sustainability concerns about overuse and environmental degradation. To support better agronomic efficiency across all classes, it is crucial to investigate not only input quantities but also application methods and timing.

As shown in Figure 16.7, the median yield for groundnut across Senegal is relatively low, reflecting widespread yield constraints in the sector. At the regional level, disparities are significant, with Diourbel exhibiting median yields of about 400 kg/ha, while Thiès reaches over 2,000 kg/ha. These differences underline the heterogeneity of performance within Senegal's groundnut sector. When compared to international benchmarks, even the higher-performing regions remain well below potential yields, highlighting considerable scope for improvement.

Median yield is used here as a more robust measure than mean yield, particularly in agricultural settings where extreme values can distort averages. Regions such as Kaolack, Fatick, and Diourbel, which are part of the traditional groundnut basin, show higher median yields. These areas benefit from favorable agroecological conditions, improved market access, and more effective agricultural extension services.

Kédougou and Tambacounda, in contrast, report some of the lowest median yields, indicating deeper structural challenges such as limited access to inputs, limited technical support, and a weaker institutional presence. It is noteworthy that land availability alone does not determine yield performance; regions with larger cultivated areas may still underperform if essential support systems are lacking.

This figure reinforces the case for spatially targeted agricultural strategies. Regions with higher median yields could benefit from value chain development and market integration, while underperforming areas require investments in basic infrastructure, input systems, and extension capacity. The median yield indicator thus provides a more transparent and equitable view of productivity, helping policymakers design interventions that are both effective and inclusive. The macro-level CGE section below

TABLE 16.2—DISTRIBUTION OF GROUNDNUT PRODUCERS BY FARM SIZE CLASS

Farm size class	Percent of producers	Area (hectares)	Yield (kg/ha)	Seed (kg)	Fertilizer (kg)
Very small (< 0.5 ha)	5.8%	0.26	1,156	21	3
Small (0.5 – 1 ha)	9.9%	0.61	649	44	6
Medium (1 – 2 ha)	31.6%	1.13	611	82	18
Large (> 2 ha)	52.8%	3.79	512	246	98

Source: PAPA (2017).

FIGURE 16.7—MEDIAN GROUNDNUT YIELD BY REGION, IN KG/HA

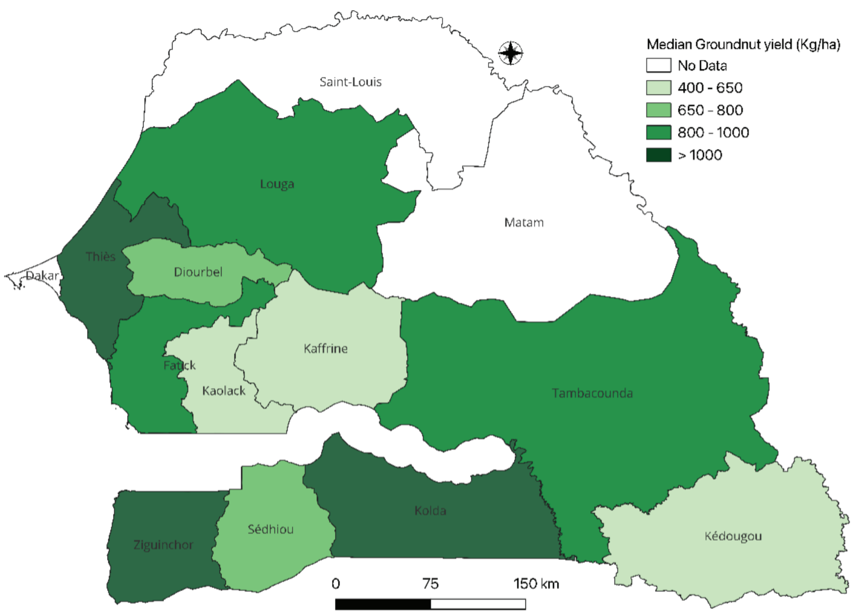
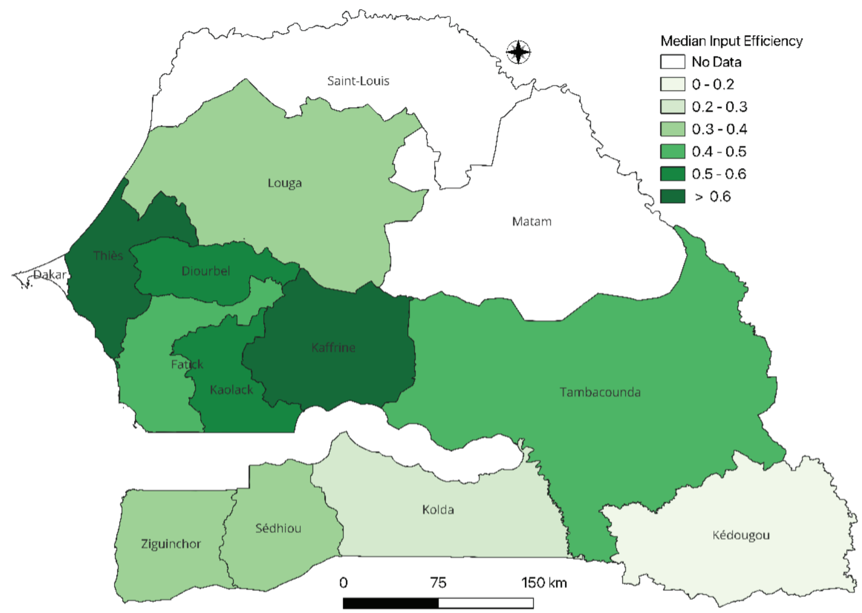


FIGURE 16.8—MEDIAN INPUT EFFICIENCY



provides a regional breakdown of total groundnut yield, as well as aggregate crop performance.

Technical efficiency

The main result of our DEA analysis is the technical efficiency measures and the implied potential gains in yields and gross margins per hectare.

Figure 16.8 maps the median input efficiency, showing how effectively typical farmers convert inputs such as land, labor, and fertilizer into output. High median efficiency values ranging from 0.5 to 0.65 indicate that the adoption of sound practices is widespread and not confined to a few elite farmers; this is especially evident in Diourbel, Fatick, and Kaolack, where the farming community benefits from cooperative networks, training, and easier access to improved seeds. In regions such as Kédougou and Matam, however, median efficiency falls below 0.4, pointing to systemic constraints. Such inefficiencies may stem from poor access to inputs, lack of mechanization, or weak extension services. The fact that median values differ significantly from mean values in some regions suggests an uneven diffusion of best practices. Policymakers should use this information to design locally appropriate solutions; these can range from peer learning systems in moderate zones to structural support in underperforming areas. Median input efficiency is a strategic diagnostic for guiding efficient, inclusive, and cost-effective interventions.

Figure 16.9 reveals how effectively typical farmers convert inputs into final output. Kaolack, Fatick, and Kaffrine display relatively high median output efficiencies, suggesting consistent use of good agronomic practices. In some regions, such as Tambacounda and Ziguinchor, however, output efficiency measures exceed 4, indicating that most farmers there operate at less than a third of their technical potential. These low efficiencies reflect challenges such as poor timing of operations, inadequate pest management, or lack of knowledge. Unlike input inefficiency, output inefficiency points to missed opportunities in translating good practices into yields. These gaps suggest the need for improved weather-aligned management and better access to advisory services. Median output efficiency thus informs both capacity-building and climate-smart agriculture programs. It highlights areas where farmers are ready for optimization and where

FIGURE 16.9—MEDIAN OUTPUT EFFICIENCY

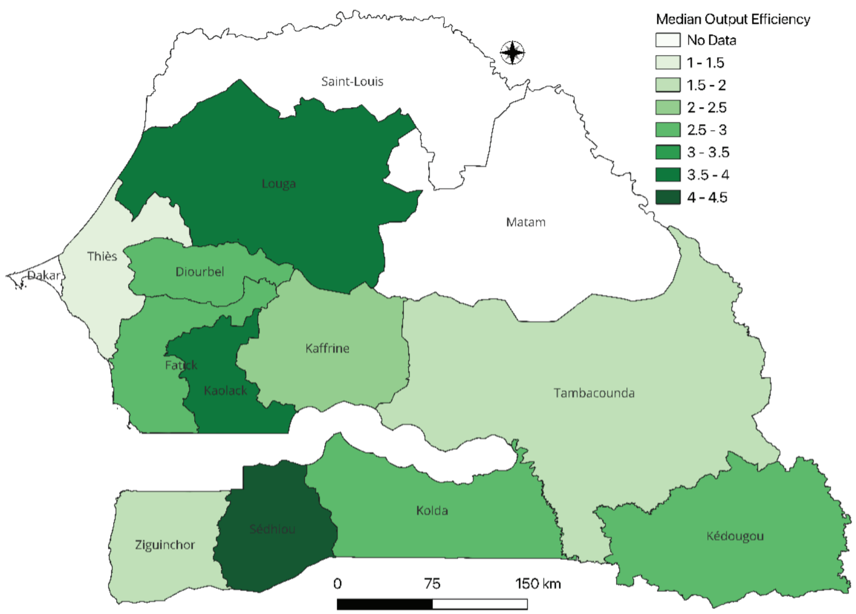
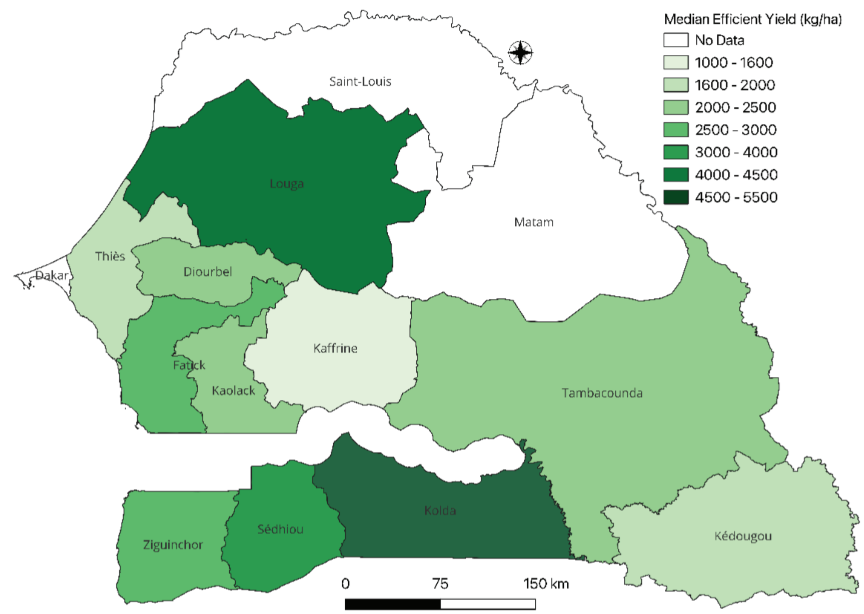


FIGURE 16.10—MEDIAN EFFICIENT YIELD PER HECTARE



foundational investments are still required. Overall, the metric provides a fair, representative view of where there is still room for improvement in productivity.

Figure 16.10 illustrates the potential yield per hectare that could be achieved if median-performing farmers were to adopt technically efficient practices, given their current resource base. Rather than expanding land or inputs, the estimate focuses on improving yield purely through better technical efficiency, such as optimized sowing time, improved spacing, and more effective pest management.

We define median efficient yield as the potential yield a typical (median) farm in a given region could attain if it were technically efficient, based on a DEA analysis. As shown in Figure 16.10, the transition to full technical efficiency results in significant yield gains. Across regions, the median efficient yield ranges from 1,500 kg/ha to over 5,000 kg/ha, whereas current observed medians are much lower, typically between 400 and 2,000 kg/ha. These discrepancies highlight the large unrealized potential in Senegal's groundnut production system. In regions such as Kaolack, Kaffrine, and Fatick, the potential median yield exceeds 2,000 to 2,500 kg/ha, reflecting favorable agroecological conditions and an enabling environment for scaling improved practices. Meanwhile, regions such as Kédougou and Tambacounda, despite lower absolute levels, still exhibit a substantial increase relative to current performance. This suggests that the primary bottleneck is technical inefficiency, rather than environmental constraint.

This analysis emphasizes the importance of focusing on efficiency gains rather than land expansion. To unlock these gains, policy efforts should prioritize knowledge transfer, farmer training, and digital tools, such as decision-support systems based on digital twin technology. The use of median efficient yield provides a realistic and equity-oriented benchmark, showing what typical farmers—not just top performers—can achieve under optimal management conditions.

Furthermore, as shown by comparing Figures 16.7 and 16.10, the corresponding gross margins per hectare under full technical efficiency also show dramatic improvements; in surveyed districts, margins increase by 120 to 400 percent per hectare. These findings reinforce the case for investing in technically sound, scalable, and inclusive interventions that close the yield gap and improve farm profitability.

FIGURE 16.11—MEDIAN REVENUE (IN FCFA) PER HECTARE

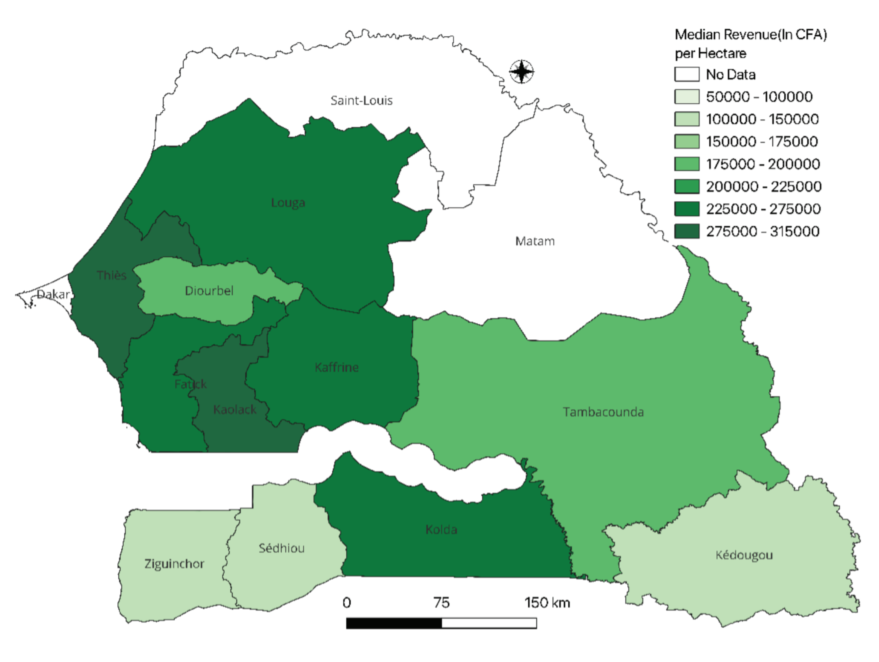


FIGURE 16.12—MEDIAN GROSS MARGIN PER HECTARE

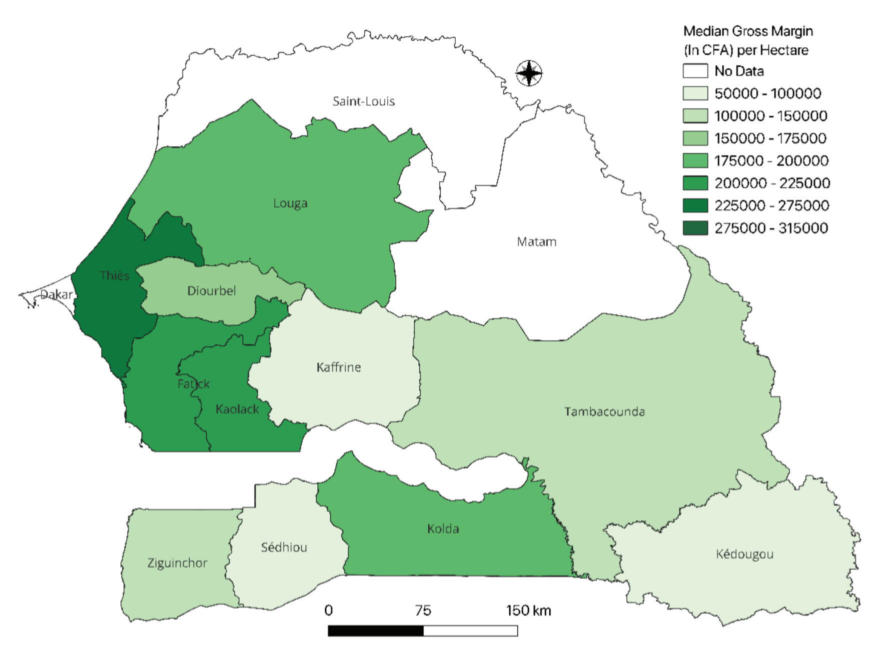


Figure 16.11 illustrates the typical groundnut farmer's earnings per hectare, with Kaolack, Kaffrine, and Fatick exceeding FCFA 250,000/ha. These earnings reflect favorable growing conditions, access to markets, and postharvest management. Regions such as Kédougou and Sédhiou, however, fall below F.CFA 150,000/ha, revealing low profitability despite similar resource use. This suggests challenges such as limited price access, insufficient storage, and limited bargaining power. Unlike total revenue, the median gives insight into income equity across farmers. In high-revenue areas, widespread benefit is likely; in low-revenue zones, economic vulnerability dominates. To raise these medians, policymakers should focus on improving access to markets and price information. Mobile platforms and cooperative sales may help increase returns for smaller producers. Median revenue is thus a critical marker for identifying income disparities and shaping inclusive value chain interventions that protect the financial sustainability of farming households.

Figure 16.12 shows profitability after subtracting costs —that is, what typical farmers truly earn. In Kaolack and Fatick, gross margins exceed FCFA 200,000 /ha (€ 305/ha), indicating well-managed input use and good prices. Tambacounda and Kédougou, however, often fall below FCFA 100,000/ha or even FCFA 50,000/ha. These low margins highlight the fragility of farm incomes in less-supported areas. Even with decent yields, high input costs or poor market access erode profitability. Margin improvement thus requires both productivity gains and cost management. Group input purchasing, mechanization services, or smart fertilization schedules could make a major difference. This figure also shows how digital tools can optimize decision-making, for example, by suggesting when to plant or which inputs to prioritize based on local conditions. Improving gross margins is essential for lifting farm households out of subsistence-level income. The median margin thus serves as a powerful indicator for prioritizing interventions that are aimed at creating more resilient and profitable farming systems.

Assessing the economy-wide impacts of digital twins

In section 4.1, based on DEA analysis, we identified significant potential to increase technical efficiency at the farm level for groundnut and other crops, such as millet and maize. These significant potential gains in agricultural productivity align with the relevant literature and represent promising pathways to more inclusive and sustainable growth in Africa.

Transforming the identified potential of DT technology into increased farm-level productivity, however, calls for an analysis of economy-wide responses to micro-level technology shocks. In the following subsection, we first explain our methodological approach. Before describing the applied quasi-dynamic CGE model, we explain the intervention logic of implementing DT technology to support individual farming decisions in Senegal.

Methodological approach

Intervention logic and definition of simulation scenarios

Based on DEA analysis, the implementation of DT technology implies large productivity gains at the individual farm level, ranging up to a 200 percent increase in gross margin per hectare for groundnut and for other crops such as millet and maize. At the farm level, productivity gains correspond to both a reduction in technical inefficiency and technical progress. To analyze how these micro-level impacts diffuse across the entire economy, we apply a Computable General Equilibrium (CGE) model. To capture specific regional impacts, we apply a CGE model with a regionalized agriculture sector. Our basic assumption is that DT technology is implemented as a public service made available to all individual farmers; a state agency, for example, collects remote-sensing climate and weather data and combines them via AI to produce area-specific biophysical and weather forecasts relevant to crop production. These forecasts serve as input to area-specific digital twin models, which, in turn, provide area-specific crop management recommendations as their central outputs. The digital twin further simulates final production and the related farm profit outcomes. To mimic the economy-wide impacts of implementing such a public DT-based farm extension service, we simulate, within the CGE model, the impact of exogenous sectoral technical progress in the corresponding crop sectors.

We simulate, in particular, four scenario types that assume technical progress of 5 and 10 percent per year for: 1) the groundnut sector (labelled by 'GNUT-5' and 'GNUT-10', respectively), 2) for all export crop sectors (labelled by 'Export-5 and 'Export-10', respectively) for all food crop sectors (labelled by 'Food-5' and 'Food-10', respectively), and 4) for all export and food crop sectors (labelled by 'Food-Export-5' and Food-Export-10', respectively).

It should be noted that, in a CGE approach with sectoral production functions, both the reduction of technical inefficiency and the technical progress that is achieved at the individual farm level translate into an increase in the total factor productivity (TFP) of the corresponding sectoral production function.

For each scenario type, we simulate a TFP increase ranging from 5 to 10 percent.

The CGE model

The original 2015 Social Accounting Matrix (SAM) for Senegal was constructed by Randriamamonjy (2021). It includes over 70 economic sectors across five regions and further distinguishes between urban and rural household types in each region. Starting with this original SAM, we constructed a SAM that includes 48 sectors and 5 regions. We derived a recursive-dynamic CGE [1] model based on the one developed by IFPRI (Diao et al. 2012; Löfgren et al. 2002). This was an economic–ecological model for analyzing the impact of the Comprehensive Africa Agriculture Development Programme (CAADP) on sustainable development in Senegal. Regionally produced goods are traded on national markets; that is, the model includes six separate commodity markets, each corresponding to a specific sector. The model includes the following economic sectors:

- Food crop production (maize, rice, cassava, sorghum, millet, wheat)
- Export crop production (groundnuts, fruit, oilseeds, other crops, vegetables)
- Other agriculture (forestry, fishing, and livestock) (oagr)
- Processing of agricultural products (food, beverages, textiles, wood)
- Other industrial production (oind)
- Public goods and services (pub)
- Private-sector services (prserv)

The model also includes three primary production factors: capital, labor, and land; capital is subdivided into agricultural and non-agricultural capital, and land is only used as a factor in input agriculture. Labor and land are traded on regional markets. A national market is assumed for capital, but agricultural and non-agricultural capital are traded on separate markets. For each sector, we assume a nested production structure in which the aggregation of primary factors into value added is modeled using a Constant Elasticity of Substitution (CES) production function. Intermediate inputs from other economic sectors are combined into an aggregate input following a Leontief function. Finally, value-added and aggregate inputs are transformed into the produced commodity at an upper nest, again following a Leontief specification. On the demand side for each regional household type, individual commodity demand

1 The detailed CGE approach is available from the authors upon request.

is derived from a Linear Expenditure System (LES). International trade is modeled via sector-specific CES functions for commodity-specific imports and Constant Elasticity of Transformation (CET) functions for commodity-specific exports. Overall, our applied regional CGE comprises 165 activities.

Following the original CGE model developed by Randriamamonjy (2021), our model is sequentially linked to a micro-poverty module, and each CGE solution delivers the corresponding poverty rates.

We selected two model outputs as relevant policy goals: **income** (GDP per capitaP) and **poverty** (national poverty headcount rate). These two goals represent a country's medium-term trade-offs along two major dimensions of the SDGs: economic growth and poverty reduction. Given the dynamic structure of the CGE, we use the linear growth rates as a measure of the goal achievements of the three selected outputs, *z*:

$$Z_k = \frac{Z_k^{2025} - Z_k^{2016}}{Z_k^{2016}}, \; k \in \{\text{GDP,Poverty}\}, \tag{4}$$

where the analysis covers the 15 years from 2015 to 2030. We further calculate average linear growth rates for each goal: $Wk = Zk/T$, where $T = 15$ is the time period. To evaluate the impact of DT on goal achievement, we calculate the percentage change in annual growth for each goal in each DT scenario in comparison to the business-as-usual (BAU) scenario.

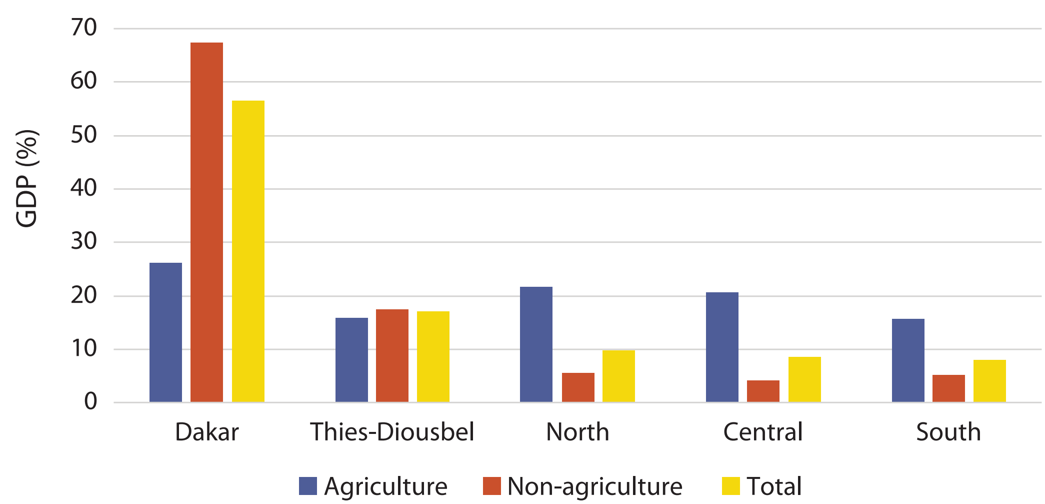
Intervention logic of the implementation of digital twins

To understand the overall intervention logic for implementing public extension services based on digital twin technologies, it is instructive to follow the CGE logic. Technically, the implementation of DT technology as a public extension service corresponds to an exogenous sectoral TFP shock within a CGE approach. Further, the TFP shocks translate into induced developments of relevant social, economic, and environmental SDG goals.

In particular, the following **intervention logic of increased agricultural productivity** (TFP) can be expected: increased TFP in the agriculture sector implies an increase in agricultural production of the products for which technical progress occurs. Accordingly, increased production implies, all else being equal, that domestic food prices will decrease due to increased domestic supply. The latter implies an increase in consumer welfare and a decrease in poverty and undernourishment. The impact of TFP on farm profits, however, is more complex. First, following the famous treadmill effect of Cochrane in agriculture might imply negative effects on farm profits depending on the market response; moreover, depending on the agricultural products for which TFP is increased and the region where the increased TFP is implemented, regional production effects for other agricultural outputs and regions may also be negative.

Regionally heterogeneous impacts of economic shocks: As the intervention logics of particular TFP shocks depend on specific regional supply and demand responses, derived impacts of common national policy shocks may differ across regions. This applies in both quantitative and qualitative terms. In some regions, for example, increased TFP stemming from the implementation of digital twin technology may induce an increase in farm incomes, while in other regions a decrease may follow. Similarly, in some regions, food crop production might induce higher farm incomes when compared to export crops, while in other regions, the reverse may be observed.

FIGURE 16.13—REGIONAL SHARES IN AGRICULTURAL, NON-AGRICULTURAL, AND TOTAL GDP IN SENEGAL



Notes: North = Saint-Louis, Matam; Central = Fatick, Kaolack, Kaffrine; South = Ziguinchor, Sédhiou, Kolda, Kédougou, Tambacounda.

Results at the macro level

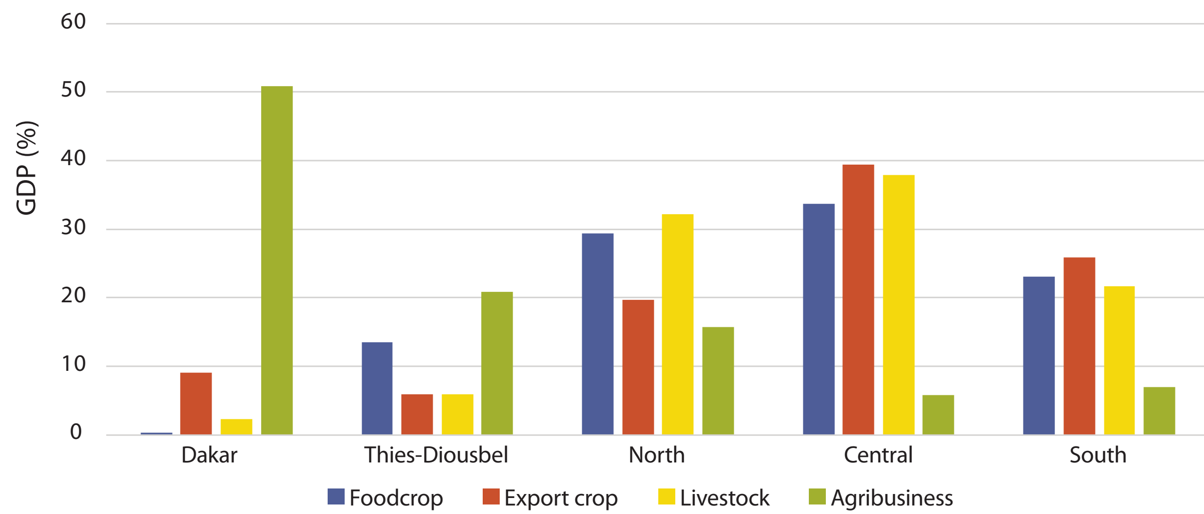
As shown in Figure 16.13, central economic activities in Senegal are concentrated in the Dakar region, with a total GDP share of almost 70 percent. This is followed by the Thiès-Diourbel region, the affluent suburb of Dakar, which has a GDP share of almost 20 percent. Interestingly, even the bulk of agribusiness activities, i.e., agro-processing and agricultural trading activities, are concentrated in these two regions.

Agricultural production, however, is mainly located in North, Central, and South Senegal, which are predominantly rural (Figure 16.14). Export crop and livestock production is located primarily in the Central and South regions of the country, while the North is dominated by food crops (mainly irrigated rice production). Together, the Central and the South regions account for 50 to 90 percent of Senegal's total agricultural production (depending on the specific product), and it is in these regions that the main groundnut and oilseed production takes place. Total groundnut production has a GDP share of 55 percent in the Central region and 31 percent in the South region, while livestock production is more evenly distributed across the three rural regions of North, Central, and South Senegal (see Figures 16.14 and 16.15).

Potential impact of digital twin technology on key SDG indicators

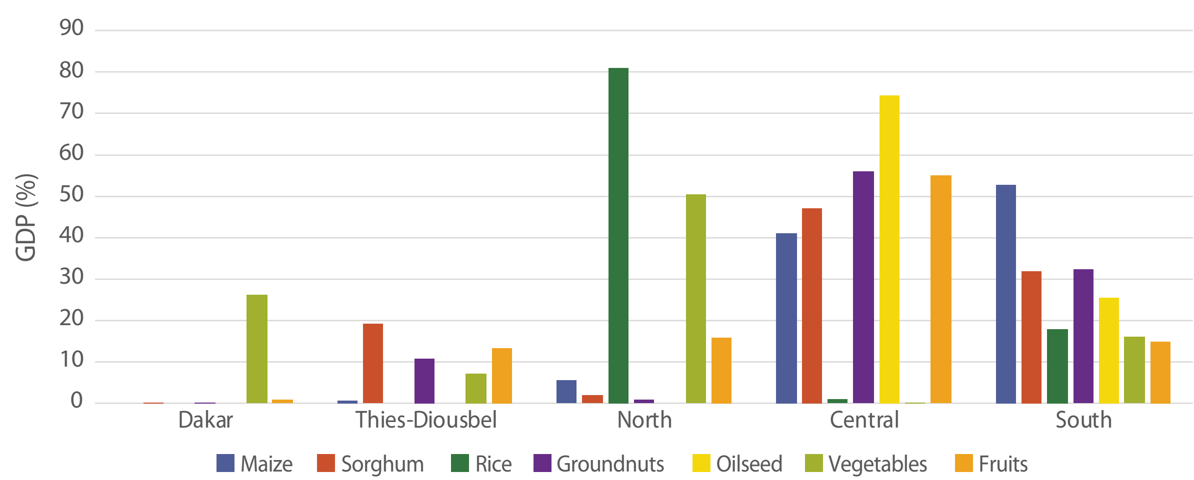
As shown in Figure 16.16, digital twin technology has a significant impact on both crop production and total agricultural production, including livestock and food processing.

FIGURE 16.14—REGIONAL AGRICULTURAL PRODUCTION, GDP SHARES OF MESOSECTORS IN PERCENT



Notes: North = Saint-Louis, Matam; Central = Fatick, Kaolack, Kaffrine; South = Ziguinchor, Sédhiou, Kolda, Kédougou, Tambacounda.

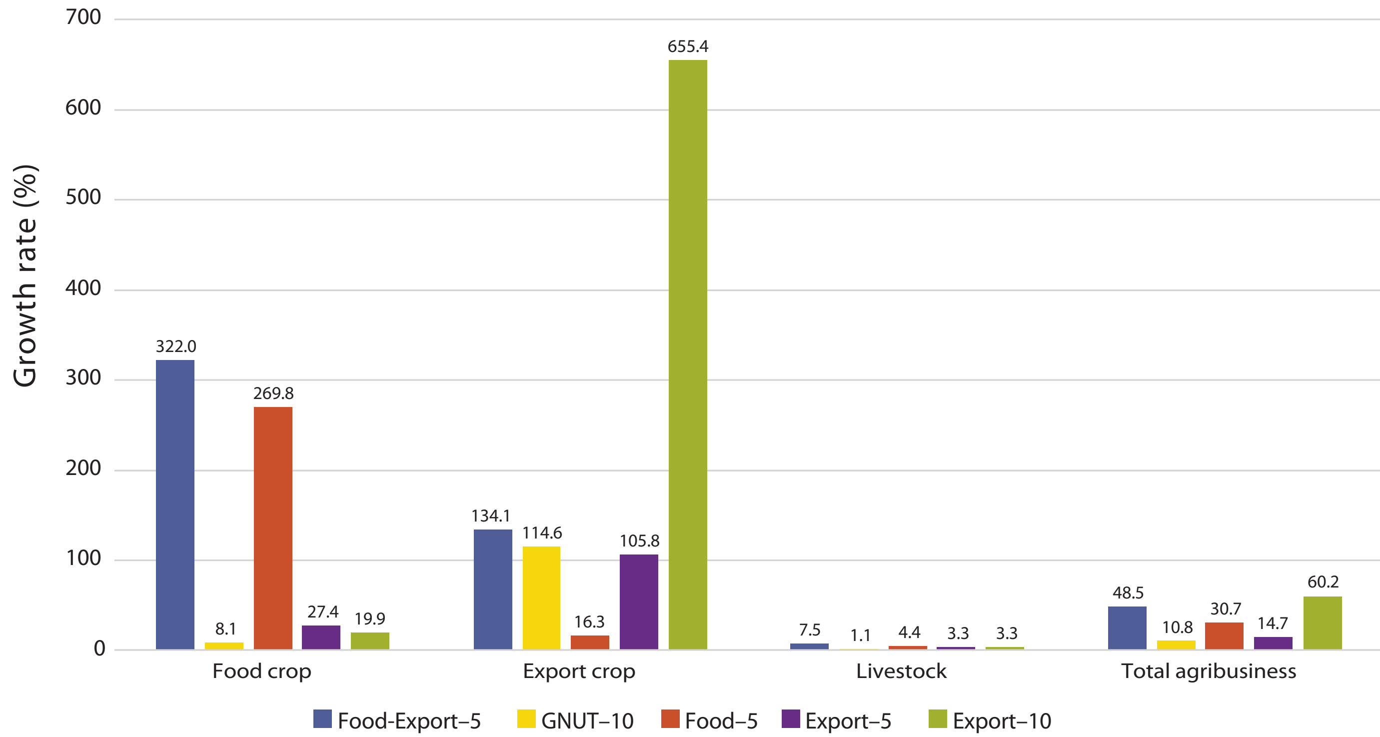
FIGURE 16.15—REGIONAL GDP SHARES BY AGRICULTURE SECTOR IN SENEGAL, IN PERCENT



Source: Senegal SAM (2021).

Notes: North = Saint-Louis, Matam; Central = Fatick, Kaolack, Kaffrine; South = Ziguinchor, Sédhiou, Kolda, Kédougou, Tambacounda.

FIGURE 16.16—IMPACT OF DIGITAL TWIN TECHNOLOGY ON CROP AND TOTAL AGRICULTURAL PRODUCTION GROWTH, IN PERCENT COMPARISON TO BAU



Source: Authors' calculations.

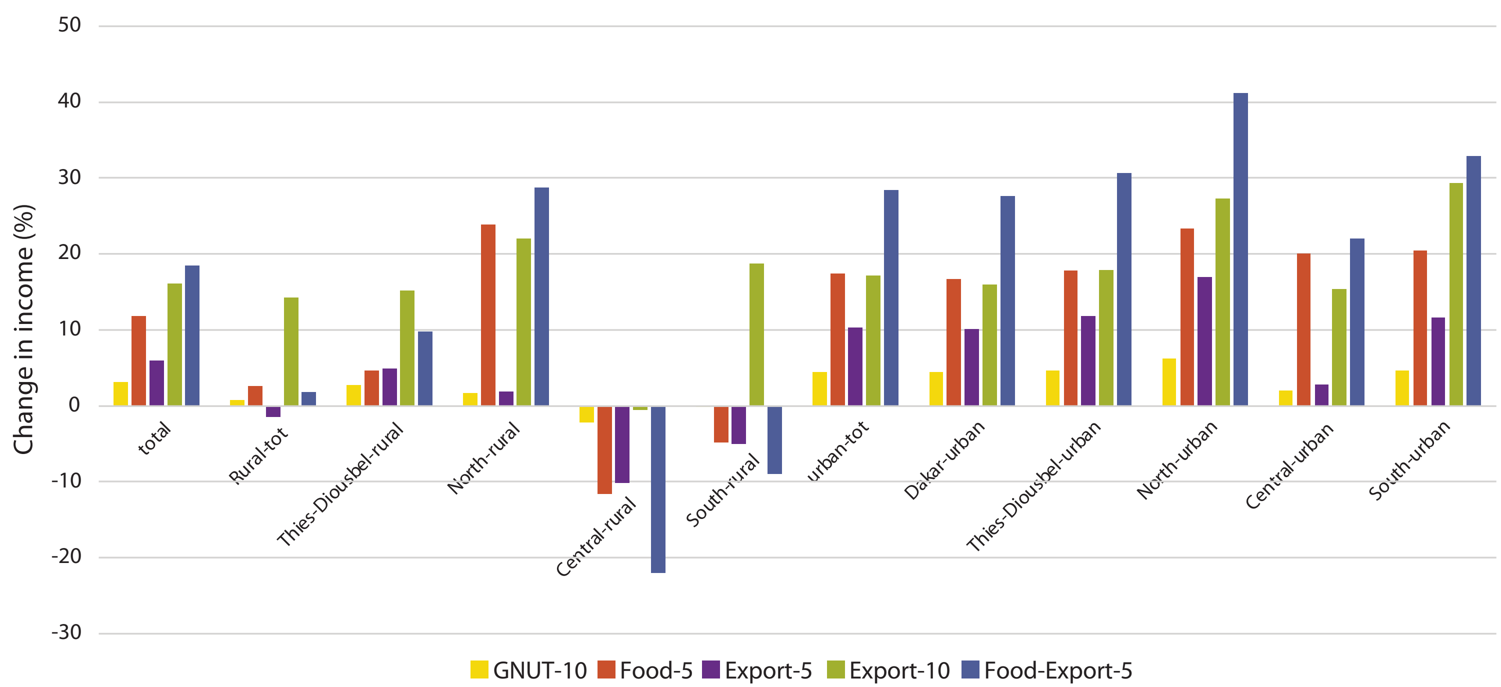
These results mirror those we observed at the farm level when applying the DEA analysis. In particular, DT technology significantly increased export crop production from 115 percent (assuming a 10 percent TFP increase only for groundnut) to as high as 655 percent (assuming a 10 percent TFP increase for all export crops), compared to a business-as-usual (BAU) scenario; however, even total agribusiness production (including food crops, livestock, and food processing) is significantly increased compared to BAU, with levels ranging from 10.8 percent (groundnut only) to as high as 60 percent (with a 10 percent TFP increase for export crops).

Beyond the impact on agricultural production, however, it is particularly interesting to observe how these production effects translate into impacts on SDG development. Figures 16.17 and 16.18 show the impact of DT technology on the development of the central SDG indicators, namely per capita income and the number of people living in absolute poverty (i.e., with an income below US$2.92 per day).

We can summarize by making the following points:

1. Focusing on groundnut only, the impacts of DT technologies on national and regional SDG developments are rather limited; this is

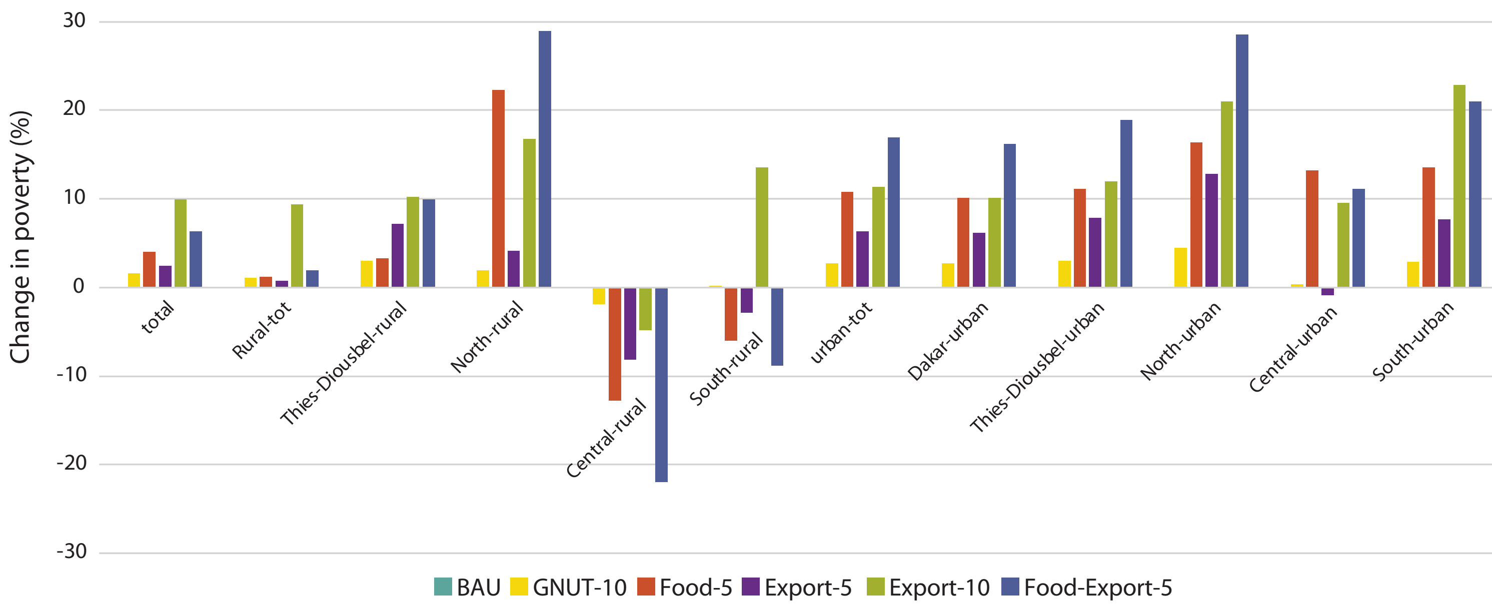
FIGURE 16.17—IMPACT OF DIGITAL TWIN TECHNOLOGY ON THE CENTRAL INDICATORS OF THE SDGS AS MEASURED BY CHANGE IN PER CAPITA INCOME COMPARED TO A BUSINESS-AS-USUAL SCENARIO (IN PERCENT)



Note: r1 Dakar: Dakar; r2 Thiès-Diourbel: Thiès, Diourbel; r3 North: Saint-Louis, Matam; r4 Central: Fatick, Kaolack, Kaffrine; r5 South: Ziguinchor, Sédhiou, Kolda, Kédougou, Tambacounda.

the case even if we assume that farm management recommendations are successfully provided to individual groundnut farmers in a timely manner via a public extension service agency. Compared to the BAU scenario, neither real per capita income nor poverty was significantly improved at the national or regional level. Notably, at least at the national level, the GDP share of groundnuts and any other individual crop is rather small, ranging from 0.9 percent for groundnuts to only 1.5 percent for fruits. Accordingly, even in the case of a high annual TFP increase of 10 percent (implying that production increased by 450 percent after 15 years), the economic impact on the overall economy will correspond to an increase of only 6.75 percent. Focusing only on groundnut production, the impact of digital twin technology on real per capita income is rather low, ranging from almost zero to 2.2 percent, compared to the BAU scenario. At regional level, however, the GDP share of groundnuts ranged from up to 6 percent in Central Senegal to 3.7 percent in South Senegal. Interestingly, even at the regional level, one cannot find any significant positive impact of implementing DT technology solely for groundnut production. In the Central and South regions, even a negative impact on farm income was found. The latter effect results from the fact that increased TFP induced a reduction in farm-gate prices that overcompensated for the positive impact of increased TFP on farm profits; this corresponds to the famous Cochrane treadmill effect mentioned above. Of course, lower groundnut prices are positive for urban consumers.

FIGURE 16.18—IMPACT OF DIGITAL TWIN TECHNOLOGY ON POVERTY (PERCENTAGE CHANGE RELATIVE TO A BUSINESS-AS-USUAL SCENARIO)



Notes: r1 = Dakar (Dakar); r2 = Thiès–Diourbel (Thiès, Diourbel); r3 = North (Saint-Louis, Matam); r4 = Central (Fatick, Kaolack, Kaffrine); r5 = South (Ziguinchor, Sédhiou, Kolda, Kédougou, Tambacounda).

2. The second point is that DT technology services result in significant impacts on both the growth of household incomes and poverty reduction, assuming that these services are provided for all crops. We thus conclude that the provision of digital twin services at the national level will result in an annual increase in TFP of 5 percent in food and export crop production; this implies that crop production roughly doubles after 15 years, causing an approximately 20 percent increase in real household income compared to the BAU scenario.

Focusing on export crops but assuming only a 10 percent annual increase in TFP implies a similar, though slightly lower, impact on average real household incomes. Notably, the impact on farm household incomes is generally much lower than on urban consumer incomes; indeed, in Central and South Senegal, which are the main agricultural regions, even a negative impact of DT technology can be observed to have a negative impact on farm incomes. As explained above, this can be attributed to the Cochrane treadmill effect. Only in the North region can similar income impacts for rural and urban households be observed; this is because, in the North, farms are specialized in rice production and therefore are net consumers of most agricultural products. The impact of DT technology on urban household incomes works by reducing the relative prices of food; that is, the impact on domestic consumer prices is more pronounced for food crops, given a higher consumption expenditure share for the former.

In contrast, farm profits, in general, depend more on export crops (which have a 5.4 percent share of GDP) than on domestic food crops (2.7 percent). The same basic pattern can be observed with regard to the impact on poverty (see Figure 16.18); however, the overall impact of DT technology on poverty is more moderate than its impact on incomes. Particularly at the national level, the poverty reduction rate is increased by only 6 percent when compared to the BAU scenario, assuming that DT technology is provided to all crops (Scenario Food-Export-5). Interestingly, assuming that DT technology is limited to export crops implies that the impact on poverty reduction compared to the BAU scenario is even higher (10 percent rather than 6 percent), assuming an annual TFP increase of 10 percent for export crops only (Scenario-Food-Export-5) . Similar to household incomes, induced poverty reductions are higher for urban households (almost 20 percent) than for rural households (at most 10 percent). Again, for rural households, the maximal reduction is observed when assuming that the TFP increase applies to export crops only, while for urban households, it is evident when assuming that DT technology is applied to all crops. At the regional level, the same pattern can be observed as seen for household incomes; that is, DT technology clearly decreases poverty in the North region, with a maximal increase in the poverty reduction rate of almost 30 percent compared to the BAU scenario. In the North region, as well, both rural and urban poverty are affected while for all other regions, the impact on urban poverty is more pronounced than on rural poverty; compared to the North, however, in other regions the impacts are comparatively lower, with maximal levels of less than 20 percent.

Conclusion

In this chapter, we examined the role of crop-soil modeling and digital twinning in supporting informed agricultural decision-making, with a focus on Europe and sub-Saharan Africa.

Modern farms are complex systems that are influenced by biophysical processes, climate, economics, and human management. To navigate this complexity, both farmers and researchers use system models to simulate crop growth and resource dynamics. Crop growth models (CGMs) have evolved from being tools for scientific analysis into practical instruments for strategic and tactical farm decisions such as planting, irrigation, and fertilization.

Over time, however, CGMs often diverge from real-world dynamics. Digital twins, that is, real-time, data-informed simulations, address this limitation through data assimilation (using, for example, ensemble Kalman filtering), thereby improving decision support by combining observational data (such as from satellites and sensors) with models.

In Europe, digital twins are already advancing sustainable farming. A notable case is the Dutch potato digital twin, which uses the Tipstar model, the FarmMaps platform, and real-time weather and sensor data. Applied on the Van den Borne farm, the system enables monitoring, forecasting, and scenario planning. It supports farmers with actionable recommendations, especially under resource constraints such as limited irrigation and regulatory pressures.

This raises the question: could DT technology significantly boost agricultural production in Africa, thereby contributing to poverty alleviation? Using groundnut production in Senegal as a case study, we analyzed the potential of digital twin technologies through a regionalized DEA and CGE framework.

Our three key findings:

1. **Digital twin technologies have high potential for productivity gains:** DT technologies can substantially increase crop yields in Senegal; however, if applied to only one crop — such as groundnut, a key export crop — their impact on the SDGs remains limited, especially in increasing income and reducing poverty. Broader application across export and food crops is thus needed to realize significant socioeconomic benefits.
2. **DT technologies have a limited SDG impact despite production growth:** While yield gains are notable, effects on household incomes and poverty are not commensurate. This is because, in relatively small sectors, the economic impact is mediated by total factor productivity (TFP). Even in agriculture-dominated regions (with a regional GDP share of 12 to 16 percent), farm income benefits are offset by price declines, which is a classic example of Cochrane's treadmill. Urban consumers, by contrast, benefit more from falling food prices.
3. **DT technologies result in only modest poverty reduction:** Poverty impacts follow similar patterns as income, but are less pronounced due to the limited market participation of poor households. National poverty reduction potential is capped at around 10 percent, with up to 30 percent in the most affected regions. By 2030, even under optimistic scenarios, lower-middle-income poverty rates could still be around 29 percent.

In conclusion, while digital twin technology can significantly enhance crop production, it is not a silver bullet for poverty eradication. To foster more inclusive growth, its deployment should be coupled with innovative organizational models such as internet-based e-cooperatives for small-scale farmers.