**Leveraging Digitalization and Technological Innovation to Enhance Agricultural Productivity and Financial Inclusion in Sub-Saharan Africa**

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**Abstract**

This paper examines the interconnected roles of digitalization, technological innovation, and financial inclusion in enhancing agricultural productivity in Sub-Saharan Africa (SSA). Using a panel dataset covering multiple countries and years, we apply a system of simultaneous equations estimated via Three-Stage Least Squares (3SLS) and Generalized Method of Moments (GMM) to account for endogeneity and dynamic effects. The empirical results reveal that information and communication technologies (ICTs) significantly boost both agricultural productivity and financial inclusion, underscoring their transformative potential. However, digital financial inclusion measured by digital finance usage shows a negative effect on productivity, suggesting a disconnect between digital financial tools and the actual needs of rural farmers. Human capital and foreign direct investment (FDI) are positively associated with productivity, while the effects of infrastructure and institutional quality are more ambiguous, often exhibiting counterintuitive or negative signs. The findings highlight the importance of context-specific policies that combine digital innovation with inclusive financial systems, education, and institutional reforms. Policy implications include expanding ICT infrastructure, tailoring digital financial services to agricultural contexts, strengthening extension systems, and aligning infrastructure investments with rural development goals. Overall, the study contributes to the growing literature on digital agriculture and inclusive development by providing evidence-based insights for designing effective rural transformation strategies in SSA.

# **Introduction**

Recent studies such as Aker & Blumenstock (2023) emphasize the transformative role of digital tools in development economics, particularly in improving agricultural value chains and financial service delivery in low-income countries. The theoretical grounding of this research lies at the intersection of the economics of technological change (Nelson & Phelps, 1966; Romer, 1990), agricultural development theory Schultz (1964), and financial inclusion frameworks (Demirgüç-Kunt & Klapper, 2013). Technological innovation, broadly defined as the process of applying scientific knowledge for practical purposes (Dosi, 1988), plays a central role in economic development by enhancing productivity and efficiency. In the context of agriculture, innovation includes the use of mobile platforms, satellite data, precision farming, and digital market platforms to reduce transaction costs and information asymmetries. These ideas align with the endogenous growth theory (Romer, 1990), which emphasizes the role of knowledge and technology in sustaining long-run economic growth.

Digitalization refers to the integration of digital technologies into everyday life and economic activity. In agriculture, digitalization facilitates timely access to market prices, agronomic advice, weather forecasts, and financial products. According to the diffusion of innovation theory (Rogers, 2003), the adoption of such technologies depends on perceived usefulness, ease of use, and socio-institutional factors. The theory also helps explain the often slow uptake of technology in rural SSA due to low digital literacy and infrastructural gaps. Financial inclusion is commonly defined as the access to and usage of affordable financial services by underserved populations (Demirgüç-Kunt & Klapper, 2013). The theoretical foundation for its link to growth is found in the financial intermediation theory (McKinnon, 1973), which posits that efficient allocation of financial resources enhances investment and productivity. Stiglitz & Weiss (1981) emphasized the critical role of information asymmetries in financial markets a theme directly relevant to understanding how digital finance can reduce such frictions for rural populations.

By integrating these frameworks, we posit that digitalization and technological innovation lower the cost of accessing information and financial services, thereby fostering inclusive growth. In rural SSA, where traditional banking and extension services are underdeveloped, digital tools can serve as substitutes, potentially boosting agricultural productivity and household welfare. The conceptual pathway links technological diffusion to improved agricultural outcomes and financial inclusion through increased access, efficiency, and reduced transaction costs.

Agriculture remains the backbone of most Sub-Saharan African (SSA) economies, contributing between 15% and 20% of GDP while employing nearly 60% to 70% of the active population, particularly in rural areas (World Bank, 2020; FAO, 2021). In some countries, such as Chad and Sierra Leone, agriculture accounts for over 30% of GDP. Despite this central role, the sector faces persistent challenges, including low productivity, subsistence-based production, and limited access to markets, finance, and technology (Diao, et al., 2021; AGRA, 2020). The majority of farms in SSA are small-scale (less than 2 hectares), constrained by weak access to credit, formal land titles, and agricultural insurance (IFAD, 2020; FAO, 2019). Additionally, agriculture is highly vulnerable to climate shocks due to its dependence on rainfall and the low use of climate-resilient technologies (IPCC, 2022). Financial inclusion remains limited in rural SSA, with only about 30% of rural adults having access to formal financial services, and the gender gap remains substantial (Demirgüç-Kunt, et al., 2018).

However, recent advances in digitalization and technological innovation offer promising avenues to address these structural barriers. Mobile money services (e.g., M-PESA), digital platforms for agricultural extension (e.g., Esoko, Tulaa), and mobile-based financial services are rapidly expanding across SSA (GSMA, 2022; CTA, 2019). These tools have the potential to enhance farmers’ access to timely information, improve risk management, and facilitate access to markets and finance. Despite these developments, adoption remains uneven, especially in rural areas where less than 30% of the population has 4G internet coverage and mobile data costs are among the highest globally (GSMA, 2022). This highlights the need for empirical research to understand the transformative potential and limitations of digital innovations in SSA's agriculture.

The objective of this research is to investigate the role of digitalization and technological innovation in enhancing agricultural productivity and financial inclusion among smallholder farmers in Sub-Saharan Africa. Specifically, this research seeks, first, to assess the impact of digital financial services on agricultural productivity and income in SSA. Second, the paper aims at identifying the main factors influencing the adoption of digital tools among rural smallholder farmers in SSA.

This study contributes to the growing literature on the intersection of digital innovation, agriculture, and financial inclusion in Sub-Saharan Africa in three significant ways. First, it provides empirical evidence on the role of digital financial services such as mobile money and mobile banking in enhancing agricultural productivity and income among smallholder farmers (Jack & Suri, 2014; Aker & Blumenstock, 2023). Second, this research advances the understanding of technology adoption in low-resource settings by identifying key determinants and constraints of digital tool uptake in rural SSA. By integrating insights from the diffusion of innovation theory and financial intermediation literature (Rogers, 2003; McKinnon, 1973), it sheds light on the socio-economic and infrastructural barriers that hinder the digital transformation of agriculture. Third, the paper contributes conceptually by bridging three theoretical traditions technological change, agricultural development, and financial inclusion and applying them in a unified empirical framework (Romer, 1990; Demirgüç-Kunt & Klapper, 2013). In doing so, it underscores the complementary relationship between digital infrastructure, human capital, and institutional support in driving inclusive agricultural transformation.

The remainder of the paper is structured as follows. Section 2 provides a brief methodological review of the digitalization, financial inclusion and agricultural productivity and Section 3 describes the method used. The estimation results are discussed in Section 4. Section 5 concludes with key policy recommendations.

# **Literature Review**

## *Digitalization and Agricultural Productivity in SSA*

Sub-Saharan Africa's agricultural sector has historically lagged in productivity due to factors such as poor access to quality inputs, limited extension services, climate variability, and fragmented markets (Diao, et al., 2019). Recent advances in digital technology offer new pathways to address these constraints. Digital agricultural innovations such as mobile-based extension platforms, precision agriculture, and remote sensing have been shown to improve farmers’ decision-making and yield outcomes. Aker & Fafchamps (2015) highlight that mobile phones reduce information asymmetries and transaction costs, allowing farmers to make more informed choices on input purchases and crop sales.

Studies such as Nakasone, et al. (2014) provide empirical evidence on how ICTs, particularly mobile phones, facilitate access to price and weather information, increasing efficiency in production and marketing. Furthermore, Fabregas, et al. (2019) conducted a meta-analysis of digital extension services in developing countries and found that digital tools can significantly improve knowledge and practices, although yield impacts remain modest and context-specific. Technological innovations in digital soil mapping, satellite-based weather prediction, and drone-based monitoring are also gaining traction. For instance, platforms like WeFarm and iCow have shown promise in Kenya in reaching smallholders with customized agronomic advice, although challenges related to scalability and digital literacy persist (Baumüller, 2018).

## *Digital Financial Services and* *Financial Inclusion*

Financial exclusion remains a significant barrier to rural development and agricultural investment in SSA. Traditional banks often avoid rural areas due to high operating costs and perceived risk. Digital financial services (DFS), particularly mobile money, have emerged as a game-changer for improving financial inclusion. Jack & Suri (2014) demonstrated that access to mobile money services (M-Pesa) in Kenya led to increased savings and a 22% reduction in extreme poverty among households, especially women-headed ones. Their follow-up study (Jack, et al., 2022) reinforced that mobile money continues to influence labor market choices and financial resilience.

Digital credit platforms such as FarmDrive, Tulaa, and M-Kopa provide alternative credit-scoring mechanisms using mobile usage data and transaction histories. These innovations help bypass the need for traditional collateral, although they raise concerns about over-indebtedness and regulatory oversight (Ghosh, 2016). Suri and William (2019) argue that digital finance facilitates investment in productive assets by reducing transaction costs and improving liquidity management. Beck, et al. (2018) also found that DFS is positively correlated with financial inclusion and consumption smoothing, especially in low-income contexts. Nevertheless, barriers such as gender digital divides, low smartphone penetration, and unreliable internet infrastructure continue to restrict DFS adoption in rural areas (Demirgüç-Kunt et al., 2022).

## *Integration of Digital Agriculture and Finance*

There is growing interest in the synergies between digital agriculture and financial inclusion. For example, platforms that integrate agricultural advisories with bundled financial products such as insurance, credit, and market access have shown potential in improving resilience and productivity. The Digital Green program in Ethiopia and the e-wallet scheme in Nigeria illustrate how combining ag-tech and fintech can enhance input access and reduce leakage (Takeshima, et al., 2017; Ogutu, et al., 2014). Despite the promise, existing research emphasizes the need for enabling policies, capacity building, and inclusive design to ensure that digital innovations benefit marginalized groups, particularly women and youth (Deichmann, et al., 2016).

Despite growing evidence, few studies simultaneously examine the interactive effects of digital financial services and technological innovation on both productivity and financial inclusion across countries. Much of the literature focuses on single-country case studies or individual technologies. Moreover, the role of institutional quality and governance in mediating these effects remains underexplored (Asongu et al., 2022). This research fills this gap by employing a multi-country panel approach and integrating institutional dimensions into the analysis.

# **Methodology**

This study adopts a quantitative empirical strategy based on panel data covering 34 Sub-Saharan African (SSA) countries over the period 2000 to 2022. The choice of panel data allows for controlling both country-specific unobserved heterogeneity and time dynamics, which are crucial for understanding the long-term impact of digitalization and technological innovation on agricultural productivity and financial inclusion. The data are compiled from several reputable sources, including the World Development Indicators (WDI), the Global Findex Database, FAOSTAT, the ICT Development Index (ITU), and the GSMA Mobile Connectivity Index.

## *Econometric Model Specification*

This study is based on the theoretical framework of the model by Mendelsohn et al. (1994), which is founded on the idea that farmers maximize the value of their land given climatic conditions and other characteristics, including socioeconomic or structural factors. The basic model is specified as follows:

$Agr\\_prod\_{it}=f\left(Temp\_{it},Temp\_{it}^{2}, land\_{it}, X\_{it} \right)$ (1)

Where 𝐴𝑔𝑟\_𝑝𝑟𝑜𝑑 is agricultural productivity, 𝑇𝑒𝑚𝑝 is the climate variable (temperature), 𝑙𝑎𝑛𝑑, refers to soil or land characteristics, and X represents the set of socioeconomic and structural variables that may influence agricultural productivity. The subscript *i* denotes the cross-sectional (individual) dimension and *t* the time dimension. In line with the aim of this work which is to examine the relationship between financial inclusion and agricultural productivity we identify financial inclusion as a relevant explanatory variable for productivity, as supported by the literature. Including other explanatory variables leads to the following econometric model specification :

$Agr\\_prod\_{it}=α+β\_{1}Ifi\_{it}+β\_{2}Temp\_{it}+β\_{3}Temp\_{it}^{2}+β\_{4}Fert\_{it}+β\_{5}Fert\_{it}^{2}+β\_{6}Agr\\_empl\_{it}+β\_{7}Land\_{it}+β\_{8}Hum\\_cap\_{it}+β\_{9}Ict\_{it}+β\_{10}Infr\_{it}+β\_{11}Inst\_{it}+β\_{12}Gdp\_{it}+β\_{13}Infl\_{it}+β\_{14}Fdi\_{it}+β\_{15}Eco\\_Free\_{it}+ε\_{it}$ (2)

Where: 𝐼𝑓𝑖 financial inclusion, 𝑇𝑒𝑚𝑝 temperature (climate variable), 𝐿𝑎𝑛𝑑 agricultural land, 𝐹𝑒𝑟𝑡 use of fertilizers, 𝐴𝑔𝑟\_𝑒𝑚𝑝𝑙 agricultural employment, 𝐻𝑢𝑚\_𝑐𝑎𝑝 human capital, 𝐼𝑐𝑡 information and communication technologies, 𝐼𝑛𝑓 infrastructure, 𝐼𝑛𝑠𝑡: institutional quality, 𝐺𝑑𝑝 economic growth, 𝐼𝑛𝑓𝑙: inflation, 𝐹𝑑𝑖 foreign direct investment, 𝐸𝑐𝑜\_𝐹𝑟𝑒𝑒 economic freedom, 𝛼 is the constant, 𝛽 are the parameters, and 𝜀𝑖𝑡 is the error term.

To account for the role of ICT in the relationship between agricultural productivity and financial inclusion, the determinants of financial inclusion are integrated into the model. This leads to the specification of a structural simultaneous equations model as follows :

$$\left\{\begin{matrix}\left(1\right) Agr\\_prod\_{it}\begin{matrix}=&α+β\_{1}Ifi\_{it}+β\_{2}Temp\_{it}+β\_{3}Temp\_{it}^{2}+β\_{4}Fert\_{it}+β\_{5}Fert\_{it}^{2}+β\_{6}Agr\\_empl\_{it}\end{matrix}\\\begin{matrix}\begin{matrix}+β\_{7}Land\_{it}+β\_{8}Hum\_{cap}\_{it}+β\_{9}Ict\_{it}+β\_{10}Infr\_{it}+β\_{11}Inst\_{it}+β\_{12}Gdp\_{it}\\+β\_{13}Infl\_{it}+β\_{14}Fdi\_{it}+β\_{15}Eco\_{Free}\_{it}+ε\_{it} \end{matrix}\\\begin{matrix}\left(2\right) Ifi=δ+τ\_{1}Ict\_{it}+τ\_{2}Gdp\_{it}++τ\_{3}Inst\_{it}+τ\_{4}Hum\_{cap}\_{it}+τ\_{5}Eco\_{Free}\_{it}+τ\_{6}Fdi\_{it}+τ\_{7}Trad\_{it}\\+τ\_{8}Infl\_{it}+τ\_{9}Exchg\_{it }+τ\_{10}Infr\_{it}+τ\_{11}Fdi\_{it} +μ\_{it} \end{matrix}\end{matrix}(3)\end{matrix}\right.$$

The determinants of financial inclusion retained in this study are: Ict (Information and Communication Technologies), Infr (Infrastructure), Inst (Institutional quality), Gdp (Economic growth), Infl (Inflation), Fdi (Foreign direct investment), Eco\_Free (Economic freedom), Hum\_cap (Human capital), Trad (Trade openness), Exchg (Exchange rate).

The determinants of financial inclusion considered in this study are as follows: Ict, information and communication technologies; Infr, infrastructure; Inst, institutional quality; Gdp, economic growth; Infl, inflation; Fdi, foreign direct investment; Eco\_Free, economic freedom; Hum\_cap, human capital; Trad, trade openness; Infl, inflation; and Exchg, the exchange rate. Here, τ represents the parameters, δ is the constant, and μ is the error term. An interaction term between ICT and financial inclusion is also introduced in Equation (1) of the final model specification to capture their joint effect.

Table 1 : Variables Definitions and Sources

|  |  |  |
| --- | --- | --- |
| **Variables** | **Definitions and Measures** | **Sources** |
| **Agr\_prod**  | Agricultural productivity |  |
| **Ifi** | Financial Inclusion Index (IFI), constructed following Sarma’s (2015) multidimensional approach. It is a composite index integrating three key dimensions of banking inclusion: (i) *Access*—measured by the number of bank deposit accounts per 1,000 adults; (ii) *Availability*—captured by the number of bank branches per 100,000 people; and (iii) *Usage*—proxied by domestic credit to the private sector as a percentage of GDP. | Authors' calculation from WDI data |
| **Land**  | Agricultural land  | FAO |
| **Temp**  | Temperature (climate proxy)  | FAO |
| **Fert**  | Use of fertilizers  | FAO |
| **Agr\_empl**  | Agricultural employment  | UNCTAD |
| **Hum\_cap** | Human capital measured through a human capital index reflecting education levels, workforce skills, health status, and innovation capacities (e.g., number of researchers and R&D expenditures) | WDI |
| **Ict**  | ICT index, incorporating fixed and mobile telephone usage, internet access, and server security  | UNCTAD |
| **Inst** | Institutional quality measured by the institutional component of the Country Policy and Institutional Assessment (CPIA), including political stability, regulatory quality, public institution effectiveness, anti-corruption measures, and civil liberties protection | UNCTAD |
| **Gdp**  | Annual real GDP per capita growth rate  | WDI |
| **Infl**  | Inflation rate, measured by the annual change in the consumer price index  | WDI |
| **Fdi**  | Foreign direct investment, measured by inward FDI flows as a percentage of GDP |
| **Eco\_Free**  | Economic freedom index  | Freedom House |
| **Infr** | Transport infrastructure, defined as the system's capacity to move people or goods efficiently, including road and rail network density and air connectivity | UNCTAD |
| **Trad**  | Trade openness, measured by the sum of exports and imports as a percentage of GDP  | WDI |
| **Exchg**  | Exchange rate  | WDI |

Table  : Descriptive statistics

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |
|  | count | Mean | sd | Min | max |
| Agr\_pro | 692 | 92.9198 | 23.7093 | 32.1600 | 183.4500 |
| Ifi | 439 | 15.6048 | 14.9973 | 0.6014 | 66.4921 |
| Land | 669 | 2212367.7892 | 3557043.7097 | 14.0000 | 19410000.0000 |
| Temp | 694 | 0.9712 | 0.4090 | -0.4779 | 2.8396 |
| Fert | 651 | 34.9528 | 87.3896 | 0.0000 | 845.0667 |
| Agr\_empl | 696 | 48.2363 | 22.1505 | 5.3178 | 91.9297 |
| Hum\_cap | 691 | 22.9747 | 8.6568 | 1.0000 | 43.9472 |
| Ict | 691 | 18.3743 | 12.4765 | 1.0000 | 74.5340 |
| Inst | 691 | 44.2846 | 12.1564 | 18.8687 | 75.1210 |
| Gdp | 720 | 1.6944 | 4.1308 | -20.8938 | 19.5083 |
| Infl | 684 | 10.9486 | 36.9017 | -16.8597 | 557.2018 |
| Fdi | 700 | 3.9088 | 5.8988 | -17.2921 | 56.2883 |
| Eco\_Free | 623 | 55.4783 | 7.9472 | 21.4000 | 77.0000 |
| Infr | 691 | 27.4072 | 15.5689 | 1.0000 | 85.9187 |
| Fdi | 700 | 3.9088 | 5.8988 | -17.2921 | 56.2883 |
| Trad | 720 | 57.4521 | 29.1147 | 7.8059 | 175.3767 |

## *Descriptive Analysis*

The descriptive analysis reveals significant heterogeneity in agricultural productivity and financial inclusion levels across the countries in the sample. The average agricultural productivity is 92.9 units, with a standard deviation of 23.7, indicating substantial structural differences in national agricultural systems. Similarly, the Financial Inclusion Index (FII), with a mean of 15.6 and a high dispersion (standard deviation of 14.99), ranges from near-zero access to financial services to relatively high levels. These disparities reflect inequalities in access to finance, which are likely to affect farmers’ ability to invest, adapt, and enhance their productivity.

Information and Communication Technologies (ICTs) also show a very uneven distribution, with an average of 18.4 users per 100 inhabitants, but extreme values ranging from 1 to 74.5. This imbalance reflects unequal digital access, which can condition the adoption of digital financial services and access to agricultural information.

The other variables confirm the structural and economic diversity of the countries studied. Agricultural land area ranges from 14 hectares to over 19 million hectares, while the use of fertilizers varies from 0 to over 845 kg/ha, illustrating stark contrasts in agricultural intensification. The macroeconomic environment is also unstable: inflation reaches extreme levels (up to 557%), and economic growth varies widely, from -20.89% to +19.51%. Significant disparities are also observed in terms of human capital, infrastructure, institutional quality, and trade openness, highlighting very diverse development and governance conditions. ICT diffusion, in particular, plays a key role not only in expanding financial inclusion but also potentially in improving productivity, by facilitating access to market information, climate data, and agricultural innovations.

These findings strongly support the use of a structural modeling approach that incorporates all these determinants to better identify the underlying interaction mechanisms. Furthermore, the graphs in Figure [insert number and title] present the correlation analysis between the dependent variable (agricultural productivity) and selected key explanatory variables, offering a preliminary view of the relationships to be further explored in the econometric analysis.




Figure 1 : Correlation Analysis

The graphical analysis of the bivariate relationships between agricultural productivity (Agr\_pro) and selected explanatory variables reveals differentiated trends depending on the factor considered. Graph (a) shows a slightly positive relationship between financial inclusion (FII) and agricultural productivity. However, the slope of the fitted line is relatively low, indicating a modest and potentially statistically insignificant link.

In contrast, Graph (b) highlights a much stronger relationship between ICT diffusion and agricultural productivity, with a clearly upward-sloping trend line. This suggests that greater penetration of information and communication technologies is positively correlated with agricultural performance—possibly by facilitating access to information, digital services, and innovation. Graph (c) displays a wide dispersion between agricultural land area (Land) and productivity, with an almost flat trend curve. This implies that the expansion of cultivated land is not necessarily associated with higher productivity. Such a pattern could reflect diminishing returns to land or underutilization of agricultural areas.

Lastly, Graph (d) suggests a weak and slightly positive relationship between average temperature (Temp) and agricultural productivity. The apparent limited impact of temperature indicates the need to incorporate this variable into a more complex framework that considers nonlinear effects or specific climate interactions. Nevertheless, while these graphical analyses provide an initial overview of the relationships between agricultural productivity and certain explanatory variables, they remain purely descriptive. They do not allow for robust causal inference, as they fail to account for the simultaneous influence of other factors or address issues such as endogeneity, unobserved heterogeneity, or multicollinearity.

Therefore, an econometric analysis is essential to isolate the specific effect of financial inclusion on agricultural productivity. This approach makes it possible to control for all relevant explanatory variables and ensure the statistical significance of the results, thereby allowing for rigorous inference and empirically grounded conclusions regarding the mechanisms at play.

## *Preliminary Tests and Estimation Strategy*

Before estimation, several preliminary tests are conducted to determine the appropriate econometric model. The Wooldridge test reveals the presence of autocorrelation in the error terms, suggesting that the estimations must account for this issue although this bias is generally less problematic in micro-panels (Baltagi, 2008). Similarly, according to Baltagi, crosssectional dependence is not considered critical when the time dimension is below 20 and is therefore not examined further in this study. In addition, multicollinearity tests show Variance Inflation Factor (VIF) values below 10, indicating no problematic correlation among the explanatory variables. The Breusch-Pagan and modified Wald tests confirm the presence of heteroskedasticity, rendering OLS estimators inappropriate. The Breusch-Pagan LM test, which compares a random effects model with a simple OLS regression, rejects the null hypothesis of homogeneity across units. Thus, a panel data model is required. Finally, a joint test for time fixed effects suggests their inclusion, as period-specific effects are statistically significant.

## *Preliminary Analyses and Estimation Strategy Selection*

The results of the preliminary econometric tests highlight several key structural features of the model, which guide the choice of an appropriate estimation method. First, the Wooldridge test for intra-individual correlation indicates the presence of significant first-order autocorrelation in the errors (*F*(1, 25) = 47.28; *p* < 0.01), justifying adjustments to correct this bias in panel data analysis. Second, the absence of serious multicollinearity is confirmed by an average VIF of 2.55, well below the critical threshold of 10, suggesting that the explanatory variables are not excessively correlated with each other.

Furthermore, the Breusch-Pagan test (*χ²* = 22.16; *p* < 0.01) and the modified Wald test (*χ²* = 3855.31; *p* < 0.01) reveal significant heteroskedasticity, implying the need for estimators that are robust to non-constant error variance. The Breusch-Pagan LM test for random effects shows that unit-specific effects (i.e., country or entity effects) are significant (*chibar²* = 33.01; *p* < 0.01), while the test for time fixed effects is also highly significant (*F*(23, 639) = 24.73; *p* <0.01), supporting the inclusion of time fixed effects in the model. Taken together, these results suggest adopting a fixed effects model with standard errors robust to both autocorrelation and heteroskedasticity in order to obtain econometrically valid estimates.

Table  : **Preliminary Tests**

|  |  |
| --- | --- |
| **Test**  | **Statistic/Result** |
| Wooldridge test for intra-individual correlation  | F(1, 25) = 47.280 |
|  | Prob > F = 0.0000 |
| Multicollinearity (VIF)  | Average VIF = 2.55 |
| Heteroskedasticity (Breusch-Pagan test)  | chi²(1) = 22.16  |
|  | Prob = 0.0000 |
| Heteroskedasticity (Modified Wald test)  | chi² = 3855.31  |
|  | Prob > chi² = 0.0000 |
| Random effects (Breusch-Pagan LM test) | chibar²(01) = 33.01  |
|  | Prob > chibar² = 0.0000 |
| Test for time fixed effects  | F(23, 639) = 24.73  |
|  | Prob > F = 0.0000 |

However, to ensure the validity of econometric inferences, it is necessary to correct for endogeneity and simultaneity biases using appropriate methods. Techniques such as two-stage least squares (2SLS), three-stage least squares (3SLS), panel GMM estimators, or the Seemingly Unrelated Regression Equations (SURE) method enhance the robustness of the estimates by accounting for interdependencies among variables and correlated errors, as recommended by Baltagi (2005), Holtz-Eakin et al. (1988), and Geishecke (2012). To address the ambiguity in the relationship between the dependent variable and the variable of interest, we employ the SURE estimator.

Moreover, introducing a dynamic specification of the model as a robustness check helps to assess the persistence of agricultural productivity. The System GMM approach (Blundell & Bond, 1998) allows for the incorporation of this dynamic structure while correcting for biases arising from omitted variables and unobserved effects, thus providing stronger grounds for causal inference.

$Agr\\_prod\_{it}=α+β\_{1}Ifi\_{it}+β\_{2}Agr\\_prod\_{it-1}+β\_{3}Temp\_{it}+β\_{4}Fert\_{it}+β\_{5}Fert\_{it}^{2}+β\_{6}Agr\\_empl\_{it}+β\_{7}Land\_{it}+β\_{8}Hum\\_cap\_{it}+β\_{9}Ict\_{it}+β\_{10}Infr\_{it}+β\_{11}Inst\_{it}+β\_{12}Gdp\_{it}+β\_{13}Infl\_{it}+β\_{14}Fdi\_{it}+β\_{15}Eco\\_Free\_{it}+ε\_{it}$

# **Empirical results**

This section discusses the main empirical findings in light of recent literature, focusing on the interplay between digitalization, technological innovation, agricultural productivity, and financial inclusion in Sub-Saharan Africa (SSA).

Table 4 : Regression estimates

|  |  |  |  |
| --- | --- | --- | --- |
|   | 3sls | 3sls | GMM |
|  | Agr\_pro | Agr\_pro | Agr\_pro |
| main |   |   |   |
| Ifi | -0.42271\*\*\* | 0.56394\* | 0.26379\* |
|  | (0.11329) | (0.28804) | (0.13799) |
| Land | 0.00000 | -0.00000 | -0.00000\* |
|  | (0.00000) | (0.00000) | (0.00000) |
| temp | -14.65121 | -18.72677\* | 6.40298\*\* |
|  | (9.70899) | (9.57108) | (3.04579) |
| temp2 | 8.48719\*\* | 10.36212\*\* |  |
|  | (4.31370) | (4.25440) |  |
| Fert | 0.11183\*\* | 0.06352 | -0.17948\*\* |
|  | (0.05701) | (0.05732) | (0.07351) |
| fert2 | -0.00036 | -0.00042 |  |
|  | (0.00028) | (0.00027) |  |
| Agr\_empl | 0.12043\*\* | 0.19650\*\*\* |  |
|  | (0.05135) | (0.05428) |  |
| Hum\_cap | 1.48974\*\*\* | 1.27777\*\*\* | -0.69978 |
|  | (0.20594) | (0.20951) | (0.45455) |
| Ict | 1.09684\*\*\* | 1.46913\*\*\* | 0.26729\* |
|  | (0.14593) | (0.17338) | (0.14110) |
| Inst | -0.68808\*\*\* | -0.65036\*\*\* | -0.29154\*\* |
|  | (0.11113) | (0.10934) | (0.13747) |
| Gdp | 0.16191 | 0.11491 | 0.50412\*\*\* |
|  | (0.20466) | (0.20083) | (0.08680) |
| Infl | -0.03399 | -0.03656 | 0.01992\*\*\* |
|  | (0.02480) | (0.02430) | (0.00483) |
| Fdi | 0.71470\*\*\* | 0.56121\*\*\* | 0.16178\* |
|  | (0.16919) | (0.17084) | (0.08410) |
| Eco\_Free | 0.25278 | 0.27550 | 0.29486\*\* |
|  | (0.18014) | (0.17650) | (0.14159) |
| Infr | -0.49073\*\*\* | -0.49358\*\*\* | -0.23883\*\* |
|  | (0.08996) | (0.08813) | (0.11171) |
| tic\_ifi |  | -0.02654\*\*\* |  |
|  |  | (0.00709) |  |
| L.Agr\_pro |  |  | 0.96767\*\*\* |
|  |  |  | (0.04291) |
| \_cons | 66.56026\*\*\* | 58.55342\*\*\* | 17.48079 |
|  | (11.84055) | (11.77371) | (14.40437) |
| q2 |   |   |   |
| Ict | 0.64886\*\*\* | 0.64887\*\*\* |  |
|  | (0.06601) | (0.06601) |  |
| Infr | 0.47109\*\*\* | 0.47127\*\*\* |  |
|  | (0.05027) | (0.05027) |  |
| Hum\_cap | -0.08566 | -0.08567 |  |
|  | (0.10747) | (0.10747) |  |
| Eco\_Free | 0.94112\*\*\* | 0.94133\*\*\* |  |
|  | (0.08447) | (0.08447) |  |
| Inst | -0.23092\*\*\* | -0.23118\*\*\* |  |
|  | (0.05950) | (0.05950) |  |
| Fdi | 0.24874\*\* | 0.24885\*\* |  |
|  | (0.09726) | (0.09726) |  |
| Trad | -0.03828 | -0.03838 |  |
|  | (0.02441) | (0.02441) |  |
| Gdp | -0.22494\* | -0.22486\* |  |
|  | (0.11587) | (0.11587) |  |
| Infl | -0.00703 | -0.00704 |  |
|  | (0.01395) | (0.01395) |  |
| Exchg | -0.00165\*\*\* | -0.00165\*\*\* |  |
|  | (0.00029) | (0.00029) |  |
| \_cons | -47.52084\*\*\* | -47.51636\*\*\* |  |
|   | (4.20069) | (4.20068) |   |
| RÂ² | 0.567 | 0.585 |  |
| ChiÂ² | 437.062 | 470.602 | 777079.784 |
| P-value | 0.000 | 0.000 | 0.000 |

## *Financial Inclusion and Agricultural Productivity*

The role of financial inclusion (Ifi) in agricultural productivity appears to be complex and context-dependent. In the main 3SLS model, Ifi exerts a significantly negative effect on agricultural productivity. This finding may reflect issues such as limited access to productive credit, financial illiteracy, or a mismatch between financial services offered and the actual needs of smallholder farmers. As shown by Koomson, et al. (2021), access to finance alone does not translate into productivity gains without complementary factors such as education, advisory services, or adequate infrastructure. In contrast, the positive and significant coefficients in the alternative specifications (3SLS and GMM) suggest that under certain conditions, financial inclusion can indeed support productivity. This aligns with evidence from Aboagye & Aidoo (2022), who found that formal financial services enhance farm output in Ghana when paired with mobile banking and agricultural extension.

## *ICT, Digital Financial Inclusion, and Technological Innovation*

The ICT index is consistently positive and highly significant across models. It positively affects both agricultural productivity and financial inclusion. This reinforces the findings of Asongu & Odhiambo (2020), who highlight that ICT penetration fosters both digital finance and agricultural value chain efficiency in Africa. Digital tools such as mobile phones improve farmers’ access to market information, weather forecasts, and financial services, as emphasized by Abay, et al. (2021). However, the inclusion of tic\_ifi a proxy for digital financial inclusion reveals a significantly negative impact on productivity. This paradox could stem from the inadequate tailoring of digital financial products to agricultural contexts, or from low digital literacy among rural farmers. As noted by Issahaku, et al. (2023), the mere availability of digital financial services is not sufficient; usability, trust, and integration into agricultural practices are critical for impact.

## *Climate Variables and Agricultural Inputs*

The estimated nonlinear relationship between temperature and productivity (negative linear term, positive squared term) suggests that moderate warming may initially harm productivity but that adaptation mechanisms could mitigate longer-term effects. This result is consistent with findings by Chisasa & Makina (2021), who emphasized the need for climate-smart agriculture in SSA. Fertilizer use, significant but with varying signs, reflects potential inefficiencies or improper application, a concern echoed in Jayne, et al. (2022), who argue that input subsidies and use without training or soil testing often lead to diminishing returns.

## *Human Capital, Infrastructure, and Institutional Quality*

Human capital shows a robust positive effect in the 3SLS models, highlighting its central role in mediating the benefits of financial inclusion and technology. This supports the findings of Tambo & Wünscher (2020), who observed that educated farmers are more likely to adopt productivity-enhancing technologies. Conversely, the negative and significant effect of infrastructure on productivity is counterintuitive but may indicate urban bias in infrastructure investment, or that agricultural infrastructure is underdeveloped or misaligned with productivity objectives. Institutions, while assumed to be supportive, show a negative relationship with both productivity and inclusion, which could reflect weak enforcement, policy inconsistency, or elite capture, as discussed by Acemoglu & Robinson (2022).

## *Dynamic Effects and Policy Implications*

The GMM model confirms the dynamic nature of agricultural productivity, with the lag of Agr\_pro highly significant (0.97). This implies that past productivity strongly predicts current performance, justifying long-term investments and policy continuity. Moreover, macroeconomic variables such as GDP and FDI are positive and significant, reinforcing the idea that external investments and stable macroeconomic environments matter for rural transformation (Yeboah, et al., 2021).

# **Conclusion**

This paper set out to investigate the interrelationships between digitalization, technological innovation, financial inclusion, and agricultural productivity in Sub-Saharan Africa (SSA), using system-based estimations (3SLS and GMM) on macro-panel data. The empirical findings offer important insights into how digital and institutional transformations can support the region's agricultural development and financial integration. Firstly, the results confirm that digitalization especially through ICT infrastructure plays a consistently positive role in enhancing both agricultural productivity and financial inclusion. However, digital financial inclusion (tic\_ifi) appears to have a counterproductive effect on productivity, suggesting that the design and delivery of digital financial services are not yet well-aligned with the realities of rural and agricultural users. This calls for a more context-sensitive and farmer-centric approach to digital finance, incorporating elements such as user education, tailored credit products, and integration with agricultural value chains.

Secondly, the role of financial inclusion (Ifi) in agricultural performance is complex. While it contributes positively under some specifications, its negative or insignificant effects in others highlight the importance of complementary conditions, such as adequate human capital, agricultural training, and supportive infrastructure. These echoes growing consensus in the literature that access alone is insufficient without usability, relevance, and complementary services.

The findings emphasize the continued importance of human capital development and climate-smart agricultural practices. The evidence of nonlinear climate effects and inefficiencies in input use (e.g., fertilizer) suggest that technological advancement must be paired with agronomic knowledge dissemination and adaptive capacity building. The strong influence of past productivity also highlights the path dependency in agriculture, reinforcing the need for sustained investment and policy continuity. The institutional quality and infrastructure are shown to influence both productivity and inclusion, but not always positively. This paradox reflects potential issues of institutional inefficiency, governance gaps, or unequal access to infrastructure investments, underscoring the need for inclusive institutional reforms and equitable rural development policies.

To effectively leverage digitalization and technological innovation for agricultural transformation in Sub-Saharan Africa, a coordinated policy approach is needed. Central to this is the promotion of inclusive digital financial services that are not only accessible but also usable and relevant to rural agricultural communities. Such services must be designed with the realities of smallholder farmers in mind considering seasonal income patterns, low digital literacy, and limited connectivity. Equally important is sustained investment in ICT infrastructure and digital literacy, with a deliberate focus on women and marginalized rural populations. These interventions help bridge the digital divide and unlock the potential of digital platforms to deliver services, training, and market access. In parallel, there is a need to strengthen agricultural extension systems by embedding financial education, climate-smart practices, and digital tool adoption into their curricula. This should go hand in hand with the development of human capital through targeted rural education programs and vocational training in agri-tech and financial management. Furthermore, governments should undertake institutional reforms aimed at increasing transparency, reducing bureaucratic constraints, and fostering accountability in service delivery. Such reforms can enhance trust and efficiency in financial and agricultural support systems. Finally, infrastructure investments particularly in transport, irrigation, and energy should be strategically aligned with agricultural development goals, ensuring that underserved rural regions are prioritized. This alignment would enable farmers to better utilize digital tools, access markets, and integrate into modern value chains, ultimately contributing to both productivity and financial inclusion.

Leveraging digitalization and innovation for agricultural transformation in SSA requires not just technological adoption, but an integrated policy framework that addresses institutional, educational, and structural barriers. Only then can digital and financial tools realize their full potential in driving inclusive rural development.

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