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THE ROLE OF MOBILE TECHNOLOGY IN AGRICULTURAL OUTPUT: EVIDENCE FROM SELECTED COUNTRIES IN EAST AFRICA

ABSTRACT

The role of agriculture in precipitating economic development is globally acknowledged and economically permissible. The purpose of the study is to investigate the extent to which mobile technology affects agricultural development in East Africa in the period 2000 to 2021. Using the fixed effects model, preferred by the Hausman test outcome, the study reveals that both mobile cellular subscription and internet usage are positively associated with agricultural production in the region, underscoring the increasing role of mobile technology in providing valuable resources and real time information to farmers in East Africa, particularly on market data, improved farming practices, and overall production. In addition, while gross fixed capital formation and employment in agriculture were found to catalyse agricultural production, climate change, here proxied by temperature change on land are negatively related to it. On the basis of these revelations, we recommend widespread investments in mobile technology infrastructure to bridge any existing gaps, especially rural-urban and gender technology gaps observable in the region. Policies to spur the widespread diffusion of mobile cellular and internet, and to promote their affordability and access would go a long way in facilitating agricultural production and in turn fight food insecurity and crisis often witnessed in East Africa. Moreover, the agricultural sector would gain from the training of the labour force and friendly policies to spur domestic investment. At the same time, the East African countries need to design policies that curtail climate change for better agricultural yields.

Key words: information and communication technology, agricultural production, East African Community

JEL Classification: Q18; Q16; O55

1. INTRODUCTION

The East African Community (EAC) Vision 2050 underscores the crucial role of the agricultural sector by designating agriculture as the key catalyst for driving industrial transformation, ensuring food security, providing employment, fostering rural development, and promoting economic well-being throughout the

region (EAC, 2022). Currently, the sector is dominated by smallholder farming that encompasses livestock, food crops, cash crops, fishing, and aquaculture. At the same time, the majority of agricultural production is subsistence-based, accounting for approximately 72%, while less than 30% comes from commercial farming. At this rate, the sector is currently operating below its potential in terms of production levels, an issue that raises concerns about food security. Available data shows that as of July 2025, East Africa hosted the largest share of Africa's acute food insecure population (*i.e.* 57.9 million people, equivalent to 35 percent of the continental total) whereas as of March 2025, over 69 million people faced acute food insecurity – almost half of the continent's total undernourished population (International Federation of Red Cross and Red Crescent Societies (IFRC, 2025). For example, in Uganda, agricultural production for essential staple crops operates at less than 40% of its attainable potential, with only about 35% of its fertile land under cultivation (Wabusa *et al*., 2025). In Tanzania, the typical food production stood at 1.7 tonnes per hectare in 2021, although it is argued that with effective agricultural management, the country has the potential to achieve yields ranging from 3.5 to 4.0 tonnes per hectare (Meya, 2021). Similarly, Adimo (2018) reveals that of the total land area in Kenya, 18% has a high to medium agricultural crop yield potential that is not utilised for production. If the popular paradigm among agricultural economists that agricultural productivity growth is necessary to "get the economy moving" is anything to go by, the observed production gaps in the East African countries, then, raise serious questions on what have traditionally been known to drive the sector. The concerns hinge on the potential for agricultural sector to release a surplus of food, labour, raw materials, capital, and foreign exchange, while simultaneously generating demand for industrial goods and services (Tiffin and Irz, 2006).

A multitude of determinants are theoretically and empirically known to drive the agricultural sector development (*e.g*. political or institutional factors, technologies, environmental and ecological factors, level of investment in research and development, and global trade reforms, *inter alia*). The current paper focuses on the role of mobile technology in agricultural production, a factor that appears to have received less attention in literature. It should be recalled that the first use of ICT to agriculture began in the 1960s, mainly via the application of computer-based data processing systems for the management of agricultural research and extension services in developed nations (Serbulova *et al*., 2019). In the recent two decades, the issue of e-agriculture was addressed in the World Summit on Information Society 2003 (Abdullahi *et al*., 2025), which made it a priority to adopt ICT in agricultural growth. Theoretically, the integration and utilisation of ICT in the agricultural sector offers potential advantages for individuals and the EAC countries, including increased productivity, enhanced service provision by government agents, creation of new employment opportunities, and optimisation of operational efficiencies. On this note, ICTs are promoted as digital platforms with the transformative potential to reach a large number of farmers simultaneously

across rural areas efficiently (World Bank, 2018). ICT usage can enhance agricultural productivity of farmers when they gain access to essential information on the best practices in real time to increase yields per hectare. It can also be used as a means to help farmers to mitigate climate change impacts and enhance food security by enabling the monitoring of climate-related data for adaptive responses (Climate Change Action East Africa, 2023). According to Awuor and Rambim (2022), farmers in Kenya and Tanzania have used mobile phones and internet to access essential market information and financial services, thereby boosting their production levels. In addition, Kremer (Casaburi and Kremer, 2019) found that the transmission of phone messages (Short Message Service, SMS), containing agricultural guidance to small-scale farmers, resulted in an 11.5% increase in agricultural yields when compared to a control group that did not receive any messages. On this note, a study by the African Development Bank (2013) suggested that African countries could boost cereal productivity by 75% by prioritising the use of ICT.

On the other hand, it has been acknowledged that countries may not achieve the optimal benefit of ICT to agricultural production if farmers have limited digital knowledge (Choruma *et al*., 2024). This means that in the presence of a persistent digital divide, ICT may not necessarily lead to increased agricultural production if the users are not empowered with the knowledge and skills needed to effectively utilise ICT tools and resources. Without this knowledge the farmer may for example, not know how and where to find openly available online solutions to improve production. On the other hand, farmers with digital skills can embrace and effectively use ICT in decision-making, resource allocation optimisation, and improvement of farming practices. This means that digital education is as a linchpin that plays a pivotal role in harnessing the ICT potential in production. The lack of digital skills in Africa could be a hindrance in obtaining real time solutions to simple agricultural challenges hampering optimal yields. Intuitively, ICT minus digital education could instead lower agricultural production. On the downside however, providing ICT education to farmers especially in the rural areas also carries with it the risk of enticing individuals, particularly the youth, to leave the sector in search of non-agricultural jobs. Such an outflux could lead to labour shortages, reduced productivity, and the potential reduction in agricultural output. Kolapo and Didunyemi (2024) complement the latter arguments by stressing that even when digital education exists, most rural areas in East Africa still experience poor cell phone and internet access whereas others are financially incapacitated to purchase smartphones, access notwithstanding.

A plethora of empirical studies have examined the relationship between ICT and agricultural output, albeit arriving at inconclusive or mixed findings (Onyeneke *et al*, 2023; Oyelami *et al*., 2022). Moreover, these studies have noticeably ignored East African Community which is home to the most progressive ICT technology and fastest growing region in Africa (Rikhotso, 2025) amidst growing food insecurity. In the recent decades, Kenya, Rwanda, Uganda and Tanzania have

witnessed a distinctively twofold increase in the adoption of new modern technologies, viz., mobile cellular and internet usage (DataReportal, 2022). A few studies that have examined the relationship between ICT and agriculture in Africa (Hopestone, 2014; Das *et al*., 2017) have not focused on the direct effect of mobile technology, and they do not capture the most recent data when the growth in mobile cellular subscriptions and internet usage has been strongest. Actually, little is known about the quantitative impact of mobile cellular and internet usage on agricultural production in the case of East Africa. Interestingly, food insecurity and food crisis still threatens the region despite the numerous concerted initiatives in the East African countries, including several ICT for agriculture initiatives developed to harness the potential of ICT in the sector (National Planning Authority, 2020). Under these circumstances, it is not clear whether the promotion of ICT is good news for agriculture or has instead swayed away the youth from agriculture and led to lower yields and food scarcity. In Kenya, a study by Marwa *et al*. (2020) revealed that the use of ICT as an agricultural extension tool by smallholder farmers has the potential to improve yields and farmers' income. A study by Nonvide (2023) focusing on Benin reveals that ICT can enhance agricultural households' welfare. Namubiru *et al*. (2018), on the other hand, argue that the use of ICT tools in accessing food security information improves households' food security status in Uganda. Mdoda and Mdiya (2022) also argued that access to ICTs can enable households succeed in increasing their agricultural production, by accessing market-oriented information, agricultural practices, climate information, information on new technologies and financial information.

The purpose of the current research is to contribute to the above literature by examining the effect of mobile technology on agricultural production in three original members of the EAC community (*i.e.* Kenya, Uganda and Tanzania) in the early 2000s when mobile technology took off, shifting from a luxury to a transformative force. It is again for this reason that the study covers the period from 2000 to 2021. Specifically, the study focuses on two ICT tools, viz., internet and mobile phones. The main contribution of the study falls under two categories. First, by examining the transformative potential of phone and internet technology, this research offers an alternative solution to boosting agricultural production. Since a low or unstable agricultural production would mean a serious hindrance to the countries' progress towards achieving the second Sustainable Development Goal (SDG) of "Zero Hunger" (SDG 2), the current analysis is timely as it provides a new layer in the advancement of this goal. Secondly, the study addresses the knowledge gap in empirical research specific to the EAC countries. In so doing, the findings would provide evidence to enable the design of policies to increase agricultural yields *via* optimizing ICT tools and resources.

The rest of the paper is organised as follows: Section 2 provides the literature review, while section 3 contains the methodology and data. The results and discussion are presented in section 4, after which section 5 presents the concluding remarks.

2. STATE OF KNOWLEDGE

2.1. THEORETICAL OVERVIEW

The current study falls in the realm of production. The first related theory, in the domain of Neoclassical models of growth, is the Solow Growth Model (Solow, 1956), which offers critical insights into the long-term determinants of economic growth and production. This model provides a foundational framework for understanding how capital accumulation, labour force growth, and technological progress influence output over time. Solow posited that in the absence of technological advancement, economies tend to reach a steady state where the output growth per worker is determined by the rates of capital accumulation and labour growth. On the downside however, critics argue that the model's assumptions about constant returns to scale and diminishing returns to capital may not fully capture the complexities of modern economies, particularly in the context of globalisation and fast technological change. Relatedly, the assumption of exogenous technological progress is a significant limitation, as it does not explain how technological advancements are generated nor how productivity changes. To overcome the above limitations, endogenous growth theories have since emerged, integrating factors such as research and development, human capital, and knowledge spillovers into the growth process. In these models, two necessary conditions for endogenous growth are: (1) increasing returns to scale over all inputs; and (2) positive impacts of non-rival inputs on the returns to investment. Intuitively, these theories explain the long run growth rate of an economy on the basis of endogenous factors as against exogenous factors of the neoclassical growth theory. On the downside however, this theory depends upon various assumptions that often seem vague or inaccurate for real-world applications.

2.2. EMPIRICAL LITERATURE

The studies in the existing literature offer a mixture of findings. For example, Onyeneke *et al*. (2023), focusing on Africa, using panel data from 32 countries from SSA, and the panel autoregressive distributed lag model as the estimation technique, find that although individuals using internet significantly increased crop production in the long run, with a percentage increase in internet patronage increasing crop production by 0.071%, a similar increase was found to significantly decrease the livestock production index both in the short and long run. Additionally, a similar detrimental impact was registered on crop production for the mobile phone subscriptions in the long run, although the contrary happened for the livestock production in the long run. At the same time, the study revealed that fixed phone subscriptions significantly increased crop production in the long run, yet they significantly decreased livestock production index in the long run.

However, the mixed evidence characterising these studies suggests the need for a deeper analysis.

On the other hand, other studies find a purely positive effect of ICT on agricultural productivity. For example, a study by Hopestone (2014) exhibited significantly positive role of telephone main lines and internet usage on agricultural production in Africa in the period 2000–2011, where the results were obtained from the employment of the Feasible Generalized Least Squares (FGLS) estimation technique. Still here, however, mobile phones exhibited a non-significant impact. On their part, Oyelami *et al*. (2022) focused on sub-Saharan African (SSA) to reveal the enhancing role of ICT infrastructure on agricultural sector performance in the long run, although this positive impact was not evident in the short term. In their view, the mere provision of ICT infrastructure may not inherently translate into immediate improvements in agricultural output; there is need to educate farmers on the continuous and effective adoption of ICT infrastructure for agricultural practices in SSA. Elsewhere, Krajnc (2020), based on panel data encompassing 60 countries over the period from 2000 to 2007, demonstrated a positive impact of ICT on agricultural production, transcending the distinctions between developed and developing nations. The authors attributed this to the ICT's potential to grant farmers easy and cost-effective access to essential information.

At country level, but at a micro-level, a study by Casaburi and Kremer (2019) focusing on Kenya, and utilizing two rounds of randomised control trials in the years 2011–2013 and 2012–2014, found out that the timely phone messages with guidance on essential agricultural tasks yielded a substantial 11.5 percent increase in crop yields when compared to a control group that did not receive these messages. Notably, this effect was particularly pronounced among farmers who lacked agronomy training and had limited interactions with sugar cane company staff at the outset. Similarly, but at a micro-level, a study by Sennuga (2020) on 200 smallholder farmers in northern Nigeria, employing a multiple-stage random sampling approach, unveiled the positive and significant impact of ICT Services in the form of Short Message (SMS), on the agricultural productivity of smallholder farmers. Remarkably, 52% of respondents reported experiencing fast increases in crop productivity as a result of these SMS reminders. Additionally, the research noted that radio and mobile phones were the most readily available ICT devices among smallholder farmers, with 97% and 85.8% accessibility, respectively. Likewise, a paper by Dagne and Oguamanam (2018) reports the importance of ICT in amplifying traditional knowledge (TK)-based agricultural production in Uganda. Mdoda and Mdiya (2022) used a multi-stage sampling in selecting 170 livestock farmers from Eastern Cape province and ICT measures, including, radio and television, mobile phones, and computers, to conclude that the use of ICTs by farmers significantly contributed to enhancing the productivity of livestock farmers. Similarly, Ndimbo *et al*. (2023) examined recent developments in the ICT sector and agricultural productivity in Tanzania and found that the increased use of

ICTs is directly linked to agricultural transformation, improved livelihoods, and increased agricultural productivity. Abdullahi *et al*. (2025), using an Autoregressive Distributed Lag (ARDL) model covering the period from 1990 to 2019 on Somalia, also show that ICT had a positive and significant relationship with agricultural productivity, indicating that ICT adoption contributes to higher production efficiency, greater land productivity, and improved labour productivity.

To the best of our knowledge, the relationship of mobile technology with agricultural production has not been explored for the East African Community. In fact, much of the discussion on ICT and their impact focus on the global north, with deficient literature on the global south (Onyeneke *et al*., 2023). It is important to conclude from the existing literature that although ICT would translate into higher productivity, a take-up of e-agriculture services, for instance, may remain partial due to barriers and digital divides among farmers in adopting digital agricultural services (Choruma *et al*., 2024). Key barriers such as limited access to technology and digital skills among farmers, lack of farmers' awareness, of training in digital literacy, lack of digital infrastructure and internet connectivity in rural areas, limited access to funding for digital initiatives in agriculture, *inter alia*, could limit the use of e-agriculture by farmers (Steensland and Zeigler, 2021). Perhaps this is the reason why the reviewed literature highlights diverse and mixed findings. On the other hand, this could be attributed to variations in time periods, study variables, data types, and methodologies. We contribute to this literature by examining the effect of ICT on the agricultural sector production in the case of East African Community members, using the recent two decades and the panel fixed effects model framework that enables us to control all variables that vary over the cross-sectional units but are constant over time.

Based on the literature review, the different hypotheses have been found.

3. MATERIAL AND METHOD

3.1. ECONOMETRIC MODEL AND DATA

The current study, based on a modified Solow growth model, used the following empirical model to investigate the effect of ICT on agricultural production in the EAC countries. The econometric model is explicitly stated as follows:

$$\ln Y_{it} = \beta_0 + \beta_1 \ln K_{it} + \beta_2 \ln L_{it} + \beta_3 CL_{it} + \beta_4 \ln Educ_{it} + \beta_5 \ln MCS_{it} + \beta_6 \ln IUI_{it} + \varepsilon_{it} \quad (1)$$

where production is (Y), K represents capital, L represents labor, CL represents Climate change, $Educ$ represents Education, MCS represents the mobile cellular subscriptions, and IUI represents internet usage.

The data covered a substantial period of 22 years, spanning from 2000 to 2021. This extended time frame provides ample observations and enhances the

potential for obtaining robust results, considering the nature of the analysis involving panel data. The data was sourced from the Food and Agriculture Organization and the World Bank Development Indicators database. The data set of the study included annual data for the following variables: Employment in agriculture (% of total employment) (modelled International Labour Organization (ILO) estimate), abbreviated as $Employment\ in\ Agric$ (as used in Berdimurodov, 2023); Gross Fixed Capital Formation (as employed in Alhaji and Gambiyo, 2023); Agriculture Value Added (*i.e.* Agriculture, Forestry and Fishing) (% of GDP), Mobile Cellular Subscriptions (per 100 people) abbreviated as MCS and Internet Usage (% of population) abbreviated as IUI, School enrolment, primary (% gross) abbreviated as $Educ$ (previously used in Luh, 2017); and Temperature change on land (°C) a measure of Climate Change abbreviated as CL (as employed in Abdullahi *et al*., 2025). The dependent variable is agricultural production and the main independent variables are Mobile cellular subscriptions, and Internet Usage as indicators of ICT. Other control variables drawn from the literature include: gross school enrolment, primary as an indicator of education; employment in agriculture as a measure of labour force employed in the agricultural sector; gross fixed capital formation in agriculture as a measure of capital stock in the agricultural sector; and, Temperature change on land as a measure of Climate change.

Agriculture includes forestry, hunting, and fishing, as well as the cultivation of crops and livestock production. The agriculture sector consists of activities in agriculture, hunting, forestry and fishing. It encompasses labour engaged in crop production, livestock farming, fishing, forestry, and related tasks. Individuals using the Internet usage (% of population) is defined as individuals who have used the Internet (from any location) in the last 3 months. On the other hand, the Mobile cellular subscriptions are defined as subscriptions to a public mobile telephone service including the number of postpaid subscriptions, and the number of active prepaid accounts. It is expected that the improvement in internet usage and mobile cellular subscription would enhance agricultural production. Education is measured by gross primary school enrolment, and represents the total number of students enrolled in primary education, regardless of age, expressed as a percentage of the population of the age group that officially corresponds to this education level. The use of gross school enrolment as a measure of Education is primarily driven by data availability, as enrolment statistics are more consistently recorded and accessible across regions and time periods. Employment is defined as people of working age who were engaged in any activity to produce goods or provide services for pay or profit, whether at work during the reference period or not at work due to temporary absence from a job, or to working-time arrangement. This variable serves as a measure of the workforce dedicated to sustaining the agricultural sector, which plays a pivotal role in the economy of EAC countries, providing livelihoods, ensuring food security, and contributing to rural development. Temperature change on land is utilised as a key indicator to measure climate change. It serves as a critical metric for tracking shifts in local and global climates over time.

3.2. ESTIMATION PROCEDURE

The empirical analysis relied on panel data from three East African Community (EAC) countries, *i.e.* Uganda, Kenya and Tanzania, covering the period 2000 to 2021. Static panel data models were chosen for this study because the number of entities (n) is smaller than the number of time periods (T). Existing literature on panel data methodologies such as that by Baltagi (2005) supports the use of static models in such contexts due to their stability and reduced risk of overfitting when T > N. Therefore, the selection between fixed effects (FE), random effects (RE) and Pooled Ordinary Least Squares (OLS) models was data-driven, with the study using the Hausman test and the Breusch-Pagan Lagrange Multiplier test to make this determination. The null hypothesis of the Hausman test is that the preferred model is RE, while the alternative is the FE model. The Hausman test checks whether random effects and regressors are uncorrelated; if they are, the RE model is preferred, and if they are correlated, the FE model is favoured. If the Hausman statistic is smaller than its critical value, the null hypothesis of uncorrelated regressors and random effects is not rejected, indicating that the RE model is appropriate.

Additionally, the Breusch-Pagan Lagrange Multiplier test was employed to assess heteroscedasticity in regression model residuals. In the context of choosing between pooled OLS and random effects models, the null hypothesis is that residuals exhibit no heteroscedasticity, indicating constant variance across observations. Conversely, the alternative hypothesis suggests varying residuals' variance across observations. The decision between models hinges on the Breusch-Pagan test results that is, a p-value below a chosen significance level (for instance 0.05) rejects the null hypothesis, indicating heteroscedasticity, favouring the random effects model. Conversely, a p-value exceeding the significance level fails to reject the null hypothesis, suggesting no heteroscedasticity, favouring the simpler pooled OLS model. To check for stationarity of the variables, two prominent unit root tests are applied: Levin-Lin-Chu (LLC) test by Levin (2002) and the Im-Pesaran-Shin (IPS) test by Im *et al*., (2003).

A series of diagnostic tests to evaluate the appropriateness of the model for the countries in EAC and validate the adherence to the standard assumptions of the regression model were used. First, to check for autocorrelation we used the Breusch-Godfrey test by Godfrey (1978) and the results are presented in Table 5, dismissing existence of autocorrelation. Second, heteroscedasticity was tested using the White (1980) test and the results are presented in Table 5, confirming homoscedasticity. Third, the Jarque & Berra (1987) test was adopted to assess whether the residuals or errors of a regression model follow a normal distribution. As the results show (see Table 5), the null hypothesis that the error term follows a normal distribution could not be rejected. Fourth, the study assessed parameter stability using the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) tests.

4. RESULTS AND DISCUSSIONS

4.1. PRELIMINARY TEST RESULTS

Table 1 provides descriptive statistics for the variables used in this study. The dataset consists of 66 observations spanning a 22-year period from 2000 to 2021 for each of the variables. Mean values for each variable represent their central tendency, while the standard deviation indicates the extent of variability around the mean. The range between minimum and maximum values illustrates the span of values for each variable. Notably, the mean values for these variables suggest that they serve as reliable measures of central tendency, as they fall within the minimum and maximum range, indicating minimal presence of outliers in the data. Among the variables, School enrolment exhibits the highest means, while Temperature change on land has the lowest. On average, Agricultural Production reflects 24.217%, signifying the percentage of agriculture, forestry, and fishing value added to GDP. Additionally, the average Gross fixed capital formation stands at 6.49 over the study period. The Internet usage and mobile cellular subscriptions have an average value of 7.332 and 44.089 respectively.

Table 1

Descriptive Statistics (%)

Variable	Obs.	Mean	Std. Dev.	Minimum	Maximum
Agriculture, value added	66	24.217	3.401	16.255	34.873
Employment in Agriculture	66	60	15.286	33.034	83.08
Temperature change on land	66	0.942	0.278	0.433	1.624
Gross capital formation	66	6.49	2.079	3.487	13.613
Mobile cellular subscription	66	44.089	33.312	0.321	122.79
School enrolment, primary	66	103.907	14.102	68.847	138.275
Internet Usage	66	7.332	7.674	0.117	31.633

Note: Obs. denotes observations; Std. Dev. is standard deviation.
Source: Author's computations.

Table 2 displays the matrix correlations among the variables investigated in the study. The table reveals no significant correlation between the variables, with the highest coefficient being 0.672, implying no issue of multicollinearity.

Table 2

Matrix of Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) Employment, Agriculture	1.000					
(2) Temperature change	-0.330	1.000				
(3) Gross capital formation	0.396	0.013	1.000			
(4) Mobile cellular subscription	-0.467	0.594	-0.069	1.000		
(5) School enrolment	0.192	-0.211	0.427	-0.322	1.000	
(6) Internet usage	-0.498	0.537	-0.178	0.672	-0.312	1.000

Source: Author's computations.

Table 3 presents the results of LLC and IPS test both at variable levels and first differences after log transformation. The LLC test and IPS test indicate stationarity of the variables at either their level or first difference *i.e.* I (0) or I (1). From the above results, Agricultural production, Temperature change and School enrolment are stationary at level (integrated of order zero). However, employment in agriculture, internet usage, mobile cellular subscriptions, and gross fixed capital formation are stationary at first difference (integrated of order one). Since the dependent variable is stationary (integrated of order zero), this study will choose between FE and RE model as well.

Table 3

Unit root test results

Test Statistics					
Variable	**LLC test**		**IPS test**		**Order of |Integration**
	Ho: Common unit root		Ho: Individual unit root		
	At level	At first difference	At level	At first difference	
Agricultural Production	-5.3195***	-13.575***	-4.5280***	-12.505***	I (0)
Employment in Agriculture	-1.1123	-5.1092***	-0.3643	-4.5882***	I (1)
Gross capital formation	-0.0417	-6.3816***	0.6479	-5.8373***	I (1)
Temperature change on land	-4.3337***	-9.9127***	-3.6250***	-8.9841***	I (0)
Internet Usage	-0.3724	-4.828***	0.3529	-4.3614***	I (1)
Mobile cellular subscription	-0.5202	-4.0971***	-1.8536	-4.1719***	I (1)
School enrolment	-1.771**	-6.5105***	-1.547**	-5.630***	I (0)

Note: All variables are in log form; ***p<0.01, **p<0.05, *p<0.1; L represents Log.
Source: Author's computations.

The results of the Hausman test and LM test are reported in Table 4. The Hausman test rejects the null hypothesis, indicating that the Fixed Effects estimator is the most efficient for the model. Moreover, the results of the LM test indicate statistical significance indicating presence of random effects thereby refusing the use of the Pooled OLS estimator. Since the Hausman test rejected the RE estimator and the LM test rejected the Pooled OLS estimator, the study considered the results of the FE estimation.

Table 3

Choosing the Best estimator for use

	Hausman test	**LM test**
Estimator	**FE vs RE**	**RE vs Pooled OLS**
Chi-square statistic	8.33	123.29
P-value	0.0155	0.0000
Decision	The null hypothesis is rejected	
Best model for use	Fixed Effects Model	

Source: Author's computations.

Table 4

Diagnostic test results

		P-values	
Diagnostic Test	Null hypothesis (Ho)	F.E Model	RE Model
LM test for autocorrelation	No serial correlation	0.381	0.140
Test for Heteroscedasticity	Homoscedasticity	0.142	0.609
Jarque-Bera test Normality	Normality	0.3618	0.180

Source: Author's computations.

Table 5 shows the results of the various diagnostic tests conducted. Breusch-Godfrey LM test for autocorrelation suggests no serial correlation, indicating no significant serial correlation in both models. The heteroscedasticity tests also suggest no significant deviation from homoscedasticity, with p-values of 0.142 for FE and 0.609 for RE. The Jarque-Bera test for Normality test indicates that both models do not deviate significantly from normality, with p-values of 0.3618 for FE and 0.180 for RE. These results suggest that neither autocorrelation, heteroscedasticity, nor non-normality are statistically significant in these models.

4.2. REGRESSION RESULTS

The estimation results are presented in Table 6. Here, the focus is on the FE outcomes, as per the Hausman test outcomes earlier presented. The RE model results are presented for robustness. Regarding our hypothesis, there is evidence that mobile technology significantly affects agricultural production. This is demonstrated by both the internet usage and mobile cellular phone indicators. Specifically, mobile cellular subscriptions showed a positive and statistically significant effect on agricultural production with p-value less than 0.05. This means that a 1% rise in mobile cellular subscriptions predicts a 0.3751% rise in agricultural production. Similarly, internet usage indicated a positive and statistically significant effect on agricultural production. Specifically, a 1% increase in internet usage would predict a 0.26377% increase in agricultural output, other factors constant. The coefficient is significant at 1% statistical level. Comparing the two indicators, the larger impact is observed in the mobile cellular phone model relative to the internet usage specification. At the same time, the results for either model are robust to the use of an alternative estimation technique, viz., the RE model, although the size of the coefficients are smaller in the latter case.

Table 5

Regression outcomes for the Fixed Effects model and the Random Effects model

Dependent variable: L. Agricultural Production			
Variable	**FE Model**	**RE Model**	**Difference GMM**
Employment in Agriculture	0.2565	0.04063***	0.2233*
	(0.53705)	(0.01002)	(0.0515)
Gross Fixed Capital Formation	0.68871***	0.5150**	0.3011**
	(0.20158)	(0.2212)	(0.5331)
Temperature Change on land	-0.18514***	-0.03857**	-0.13011**
	(0.0576)	(0.1777)	(0.0312)
Internet Usage	0.26377**	0.0105***	0.1913**
	(0.1296)	(0.00294)	(0.03321)
Mobile Cellular Subscriptions	0.3751**	0.3461***	0.3007**
	(0.07474)	(0.1074)	(0.0521)
School Enrolment, primary	0.22359	0.0203	0.2316
	(0.12738)	(0.0102)	(0.0520)
Agricultural Production (lag)			0.7652***
			(0.0823)
Constant	0.21369***	0.1199***	0.2321**
	(0.01652)	(0.03982)	(0.06220)
Instruments			18
HansenJ-test			[0.253]
AR(1)			[0.000]
AR(2)			[0.621]
F-test (Prob.>chi2)	9.37[0.0032]		
Wald-test (Prob.>chi2)		5.975 (0.0098)	
Observations	66	66	66
CUSUM test	YES	YES	YES

Note: All variables are in log form; Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Source: Author's computations.

Additionally, as expected, the coefficient of gross fixed capital formation was positive in the regression. Specifically, a 1% increase in investment is associated with about 0.68871 percent change in agricultural production. The coefficient is highly significant at 1% statistical level. Similarly, temperature change on land had a significant negative effect on agricultural production. That is, a 1%t increase in climate change predict a 0.18514 percent decrease in agricultural production. Still, the coefficient is highly significant at 1% conventional level.

The finding of the positive influence of mobile cellular subscriptions on agricultural production suggested that the widespread adoption and utilisation of mobile phones positively influence agricultural output in the EAC countries and could be an important channel to strengthen the sector if food insecurity is to be solved in EAC. This finding is consistent with the study by Min *et al*. (2020), where it was revealed that the use of mobile phones among farmers had a significant impact on the transformation of rural economies. This impact included

facilitating off-farm employment, the cultivation of non-grain crops, and increased production. One possible explanation for the positive relationship in the EAC countries is that mobile phones have become essential tools for individuals and firms in the agricultural sector, enabling them to access critical information and resources. With mobile technology, farmers can receive timely market information, weather updates, agricultural best practices, and extension services, which can significantly increase their production.

Similarly, the finding of the enhancing role of internet usage in the agricultural production underscores the growing importance of internet usage in precipitating production, perhaps because it offers individuals and firms in the agricultural sector valuable resources and information. Online tools enable farmers to make informed decisions on crop management, weather, and market prices (Choruma *et al*., 2024). This increases efficiency, crop yields, and market access, ultimately improving agricultural production for farmers. However, the small coefficient of internet usage, relative to mobile phones, would likely suggest that only a few individuals in the sector utilise the internet for production purposes. Nevertheless, the finding aligns with what Nguyen *et al*. (2023) documents for rural Vietnam.

Besides mobile technology, the study revealed several other important findings worth discussing. First, the finding that investment, measured by gross fixed capital formation, orchestrates agricultural production would suggest that the East African countries have not invested in agricultural infrastructure in vain. The higher levels of investment in fixed capital, such as infrastructure like roads and machinery, and particularly those linked to agriculture, have benefited agricultural production. One possible explanation could be that investments in fixed capital such as feeder roads, telecommunication networks and machinery like tractors, irrigation systems in the EAC countries can lead to increased agricultural productivity by providing the necessary tools and resources for farming activities, consequently leading to increased production.

Finally, the finding that temperature change on land has a detrimental effect on agricultural production may be attributed to the adverse impacts of climate change, such as extreme weather events, prolonged droughts, or shifting temperature patterns evident in the EAC countries. These factors negatively affect crop yields and overall agricultural production, given that much of the production in these EAC countries is rain-fed (EAC, 2022). A previous study by Guo *et al*. (2022) revealed that changes in temperature played a significant role in variations in agricultural output.

4.3. ROBUSTNESS CHECK

The likelihood of the past levels of agricultural performance affecting the current levels may not be inadmissible, hence leading to endogeneity concerns. In order to address this issue and to check for robustness of the findings from random

effects, we employed the difference GMM estimation technique, well-known for taking care of endogeneity. The results, as presented in Table 6, appear to confirm the importance of mobile technology on agricultural production. The relevant coefficients on mobile phone and internet usage are significant at 5% statistical level. It is only the magnitude that appears to differ. Otherwise, our conclusion of the importance of mobile technology remains intact.

5. CONCLUSIONS

This study examined the effect of information and communication technology (ICT) on agricultural production, analysing data from three countries in the East African Community in the period 2000 to 2021, by employing the fixed effects estimation technique. The random effects method was also adopted to check for the robustness of the results. Besides, several diagnostic tests were carried out to ensure reliability robustness. The study's key finding indicated that both mobile cellular subscription and internet usage influence agricultural production. Relative to mobile phones, however, the impact of internet usage on agricultural production is observed smaller in magnitude. While gross fixed capital formation was found to propel agricultural production in East African Community, temperature change on land has a detrimental effect on agricultural production.

These findings hold important policy implications. First, the Governments of EAC countries should facilitate the diffusion of mobile cellular subscriptions and internet use, especially in rural areas where agriculture is majorly practiced. The diffusion of mobile cellular and internet could involve expanding network coverage and improving access and affordability of mobile and internet services. Investing in rural telecommunications infrastructure and deploying modern connectivity solutions would thus be a good venture into catalysing agricultural production. At the same time, we are in support of policies that aim at the development and dissemination of mobile and internet-based applications tailored to the agricultural sector's needs, providing weather forecasts, market prices, agricultural tips, and financial services. The implementation of e-agriculture ought to be prioritised if countries in East Africa are to solve the food insecurity challenge. We advocate for policies that address any existing barriers to internet use such as the prioritisation of investments in rural broadband infrastructure to extend high-speed internet coverage to remote agricultural regions through public-private partnerships, subsidies for internet service providers to expand their networks in rural areas, removal of any digital tax on internet and mobile phones so as to reduce internet cost. Relatedly, targeted programs to promote digital literacy and inclusion among farmers and rural entrepreneurs should be promoted. By overcoming these barriers, farmers will gain access to online resources, market information, e-commerce platforms, and digital tools that they can use to enhance agricultural productivity, improve market access,

and increase production in the sector. The EAC Agricultural and Rural Development Policy should be fully implemented by member countries to catalyse agricultural transformation via ICT technology. Additionally, to mitigate the negative effects of climate change, particularly temperature changes, governments should promote the adoption of efficient irrigation systems to optimise water use and sustain agricultural resilience.

The current study is not without limitations. First, the study did not include alternative ICT indicators such as radio, computer and television usage due to data unavailability. Perhaps, future studies would venture into this direction if data becomes available. In any case, our findings can be considered reliable since the utilised indicators are the major types of ICT types adopted in East Africa, as earlier presented in the discussion. Future studies would also look into analysing separately the various sub-sectors of agricultural production such as Fisheries, Crop Production, and Animal Husbandry, since each of these subsectors presents unique characteristics, with distinct production needs and market dynamics across different EAC countries. The current study was on the aggregate production that incorporates all these – crop and livestock production. The other limitation is that while individual countries within the EAC may face specific challenges, such as varying climate and infrastructure issues, the study never took this diversity into perspective and only focused on the whole of East Africa to benefit from the advantages of panel analysis. Future studies would look at individual countries to determine the specific effects for each country. Nevertheless, our findings remain intact and reliable given the strong methodological approach, checked for robustness using alternative approach but which also involved performing diagnostic tests. Finally, the finding that employment in agriculture had a positive but statistically insignificant effect on agricultural production would necessitate further analysis, though we envisage little change if the theory of diminishing returns to labour is to go by.

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