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Research Article

Analyzing the effects of ICT infrastructure adoption on agricultural output in Nigeria: an error correction model approach

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Abstract: This study examined the effects of ICT infrastructure adoption on agricultural output in Nigeria. Annual data on fixed telephone subscriptions, mobile phone subscriptions, internet usage, ICT goods import and some production variables spanning from 1994 to 2023 were used for the study. The unit root test of stationarity of each variable was obtained using the Augmented Dickey–Fuller (ADF) while the existence of long-run and short-run relationship among the variables was established using Engle and Granger 2-step approach. The ADF results revealed that all variables were integrated order of one I(1) and the error term of the long-run regression was stationary at level . Then, we implemented error correction model (ECM) to examine the short-run relationship between agricultural output and the ICT variables under consideration. The overall estimated result showed a significant long-run relationship between agricultural output and mobile phone subscriptions (=0.027), internet usage (=2.593), ICT goods import (=2.357), and short-run significant relationship with only ICT goods import (ϕ=0.996) and mobile phone subscriptions (ϕ=0.160). Fixed telephone did not have significant influence on agricultural output both in the short-term and long-term. The study suggests implementation of policies that will improve the existing level of ICT facilities for enhancement of more agricultural output.

Keywords: Adoption, Agricultural output, Error correction model, ICT infrastructure, Nigeria

1. Introduction

In recent decades, the advancement in Information and Communication Technology (ICT) has led to significant transformation in labour productivity across various sectors of the global economy (Nakasone et al., 2014; Olaniyi, 2018; Kante et al., 2019). The agricultural sector, a cornerstone of Nigeria economy over the years has been part of this trend, as ICT infrastructure increasingly penetrate both rural and urban areas (Oyelami et al., 2022). The agricultural sector contributes approximately 23% to the nation's Gross Domestic Product (GDP) between January and March 2021, and employs over 70% of the population, predominantly at the subsistence level (Showole & Hashim, 2014; FAO, 2021; Azubuike et al., 2023). Inspite of these important roles, the sector is still facing problems of low productivity, market inefficiencies, inadequate extension services, significant post-harvest losses, limited access to financing, and minimal technological adoption (FAO, 2021). Given the growing presence of ICT infrastructure across Sub-Saharan Africa, particularly in Nigeria, and their potential to enhance operational efficiency (Bankole et al., 2013; Oyelami et al., 2022), the integration of ICT infrastructure into agricultural systems present a strategic opportunity to improve productivity, streamline operations, and increase profitability within the sector (Quandt et al., 2020; Sennuga et al., 2020; Onyeneke et al., 2023).

A myriad of technologies used to facilitate information flow and enable communication are collectively referred to as Information and Communication Technology (Okyere & Mekonnen,

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2012). ICT infrastructure involves various devices and systems, including digital platforms, mobile phones, internet connectivity, remote sensing technologies and Geographic Information Systems (GIS) that can be used to receive, process, store, and share information, thereby facilitating innovative agricultural practices. They also include software, hardware, and multimedia devices such as radio, television, and digital cameras, and any medium capable of transmitting information in the form of voice, data, text, or images (May, 2012; Oluwatayo, 2014; Saidu et al., 2017). According to Yonazi et al. (2012) and Chavula (2014), the application of ICT in agriculture has tremendously facilitated the adoption of modern technologies and enabled the precise application of inputs such as fertilizers, pesticides, energy, and water, thereby ensuring the optimal use of limited resources.

Furthermore, the use of ICT in farming activities has substantially improved access to information on production inputs, market intelligence, and global markets for stakeholders in agriculture (Arvin et al., 2021). Likewise, the ongoing campaign on sustainable and precision agricultural practices, particularly in sub-sahara African countries can be largely credited to the expansive spread of ICT infrastructure. Adoption of e-agriculture across different stages of production process has been increasingly widespread, enabling farmers to access timely and relevant information that enhances productivity (Amarnath et al., 2018; Dong et al., 2021). ICT infrastructure now plays a pivotal role in facilitating production processes, inventory management, price monitoring and dissemination, and post-harvest handling, ultimately contributing to the maximization of agricultural output. Moreover, ICT has improved rural household knowledge and decision-making by enhancing access to production-related data, thereby empowering farmers to make more informed choices (Radoglou-Grammatikis et al., 2020, Liu et al., 2021). ICT has emerged as an effective solution to the persistent challenges confronting agriculture in developing countries, including limited market access, inadequate information management, low productivity, and insufficient farmer income, particularly through its role in export facilitation (Akpa & Chabossou, 2024).

In spite of numerous benefits of ICT in agricultural development, Africa continues to remain backward in its adoption, primarily due to poor financial investment and shortage of the technical expertise required to deliver digital technology services (Onyeneke et al., 2023). However, in the Nigerian context, adoption of basic ICT infrastructure such as fixed telephone, mobile phones, internet service, among others for disseminating agricultural information is becoming prevalent. Oyelami et al. (2022) reported a substantial increase in mobile phone subscriptions, rising from 18.59 million in 2005 to over 172 million by 2018. Even though this growth reflects a promising trajectory, the use of ICT in agricultural production is below expectations, especially when evaluated against its transformative potential in driving agricultural development. Several persistent barriers undermine the effective utilization of ICT in Nigeria's agricultural sector. These, among others, include poor internet system connectivity, unreliable electricity supply, high costs of commercial internet access, and limited availability of accessible and impactful agricultural databases (Showole & Hashim, 2014). Moreover, the high cost of internet-enabled smartphones, widespread illiteracy, linguistic diversity, underinvestment in ICT infrastructure, and the threat of cybercrime, especially in mobile money transactions, further constrain ICT implementation (Ejemeyovwi et al., 2017). Other critical challenges include insufficient ICT facilities, a dearth of trained professionals, weak integration and harmonization of agricultural knowledge, and negative farmer perceptions, all of which continue to hinder ICT adoption and its scalability in the country (Saidu et al., 2017).

Several studies have explored the relationship between ICT and agricultural sector performance in Sub-Saharan Africa (Oyelami et al., 2022; Onyeneke et al., 2023; Akpa and Chabossou, 2024). These studies generally found a positive long-run relationship between ICT infrastructure and agricultural sector performance. However, research on ICT adoption and its impact on agricultural sector performance in Nigeria remains limited, and much of the existing literature is either sub-sector specific like crop production or focused on specific geographic locations (Olaniyi et al., 2013; Ejemeyovwi et al., 2017), neglecting aggregate national trends. Given Nigeria's distinct economic position within the Sub-Saharan Africa region, there is a pressing need for a country-specific analysis. Such an analysis will provide an empirical basis for evaluating the current state of ICT infrastructure and its contribution to agricultural productivity, while also identifying the gaps that need urgent interventions and strategic investment. More importantly, evaluating the agricultural sector in aggregate, rather than focusing on specific sub-sectors or locations addresses a critical limitation in the existing body of literature and supports more robust, inclusive policy formulation. Accordingly, this study investigates the effects of ICT infrastructure adoption on agricultural output in Nigeria. The research is particularly significant, considering the recent expansion of ICT across multiple sectors and the urgent need to understand its implications for agricultural development. Findings of this research are expected to provide valuable insights for stakeholders and inform future strategies aimed at enhancing ICT driven transformation in Nigeria's agricultural sector.

2. Materials and methods

2.1. Data source

The study relied on time series secondary data consisting annual observations on Nigerian agricultural output, ICT infrastructure and other related variables to the study for the period of 1994-2023. The data on fixed telephone subscriptions (FIXTEL), internet usage (INTERUSE), mobile cellular subscriptions (MOBCEL), ICT goods import (ICTGIMP) and agricultural land (AGRLAND), were obtained from world bank's world development indicators (WDI). Data on agricultural output (AGROUTPUT) and other variables such as fertilizer consumption for agricultural productivity (FERTCON), agricultural labour used (AGRLAB) and pesticide used (PESTIUSE) were obtained from FAOSTAT. Variables such as agricultural AGRLAND, FERTCON, AGRLAB and PESTIUSE were included in this study in order to avoid studying the effect of ICT infrastructure on agricultural output in isolation of other essential variables in agricultural production process.

2.2. Econometric analysis

Data collected were analysed using descriptive and inferential statistics. The Augmented Dickey–Fuller test was used to analyze the stationarity or non-stationarity of the time series, while the Engle and Granger 2-step approach was deployed to examine the long-run equilibrium and short-run dynamic among the variables. Short-run model diagnostics such as Breusch-Pagan-Godfrey heteroskedasticity test, Jarque-Bera statistic for normality test, and Breusch-Godfrey serial correlation test were carried out to justify the choice of our analytical model. The choice of these analytical tools was based on stationarity behavior of macro variables considered for this study.

2.2.1. Augmented Dickey-Fuller (ADF) test of unit root

The use of time series data is often associated with the possibility of obtaining spurious regression because of the presence of some non-stationary variables among the variables under study. Therefore, testing for stationarity of variables included in our econometric models becomes necessary. The Augmented Dickey-Fuller(ADF) test was employed to investigate if the time series variables have a unit root or not. The ADF test is a modification of the Dickey-Fuller (DF) test proposed by Maddala and Wu (1999), and it involves the augmentation of DF equation by including the lagged values of the regresand variable. The study made use of Akaika information criterial for lag selection, and the ADF models for the time series are given as:

Agricultural output:

$$\Delta \mathrm{AGROUTPU} = \alpha_0 + \alpha_1 t + \beta \mathrm{AGROUTPUT}_{t-1} + \textstyle\sum_{i=1}^{p} \delta_i \, \Delta \mathrm{AGROUTPUT}_{t-1} + e_{it} \ldots\ldots\ldots (1)$$

Fixedtelephone:

$$\Delta \mathrm{FIXTEL} = \alpha_0 + \alpha_1 t + \beta \mathrm{FIXTEL}_{t-1} + \sum_{i=1}^{p} \delta_i \, \Delta \mathrm{FIXTEL}_{t-1} + e_{it} \ldots\ldots\ldots\ldots (2)$$

Internet usage:

$$\Delta \mathrm{INTERUSE} = \alpha_0 + \alpha_1 t + \beta \mathrm{INTERUSE}_{t-1} + \sum_{i=1}^{p} \delta_i \, \Delta \mathrm{INTERUSE}_{t-1} + e_{it} \ldots\ldots\ldots (3)$$

Mobile cellular:

$$\Delta \mathrm{MOBCEL} = \alpha_0 + \alpha_1 t + \beta \mathrm{MOBCEL}_{t-1} + \sum_{i=1}^{p} \delta_i \, \Delta \mathrm{MOBCEL}_{t-1} + e_{it} \ldots\ldots\ldots\ldots (4)$$

ICTgoods import:

$$\Delta \mathrm{ICTGIMP} = \alpha_0 + \alpha_1 t + \beta \mathrm{ICTGIMP}_{t-1} + \sum^{p} \delta_i \, \Delta \ \mathrm{ICTGIMP}_{t-1} + e_{it} \ldots\ldots\ldots\ldots (5)$$

Agric land:

$$\Delta \mathrm{AGRLAND} = \alpha_0 + \alpha_1 t + \beta \mathrm{AGRLAND}_{\,t-1} + \sum_{i=1}^{p} \delta_i \, \Delta \, \mathrm{AGRLAND}_{\,t-1} + e_{it} \ldots\ldots\ldots (6)$$

Fertilizer consumption:

$$\Delta \mathrm{FERTCON} = \alpha_0 + \alpha_1 t + \beta \mathrm{FERTCON}_{\,t-1} + \sum_{i=1}^{p} \delta_i \, \Delta \mathrm{FERTCON}_{t-1} + e_{it} \ldots\ldots\ldots (7)$$

Labour:

$$\Delta \mathrm{AGRLAB} = \alpha_0 + \alpha_1 t + \beta \mathrm{AGRLAB}_{\,t-1} + \sum_{i=1}^{p} \delta_i \, \Delta \mathrm{AGRLAB}_{t-1} + e_{it} \ldots\ldots\ldots\ldots (8)$$

Pesticide:

$$\Delta \mathrm{PESTIUSE} = \alpha_0 + \alpha_1 t + \beta \mathrm{PESTIUSE}_{\,t-1} + \sum_{i=1}^{p} \delta_i \, \Delta PESTIUSE_{t-1} + e_{it} \ldots\ldots\ldots\ldots (9)$$

Where AGROUTPUT stands for agricultural output measured as a proxy of net production index for total production output from both crop and livestock production, as well as other agricultural outputs, FIXTEL represents fixed telephone adoption measured as number of people that subscribed for Fixed telephone, INTERUSE means internet usage measure in percentage of total population, MOBCEL connotes mobile cellular usage measured in number of people that subscribed for mobile cellular, stands for ICT goods imports measured in % of total goods imports, agricultural land captured as total area of land used for agricultural purposes in square kilometer, FERTCON represents fertilizer consumption and it is taken to be the quantity of metric tons of plant nutrients used,AGRLAB represents agricultural labour measured as a proxy of employment in agriculture in percentage of total employment, PESTIUSE indicates the quantity of pesticide used for agricultural purpose in tons, , is the estimated coefficient of time series variables, represents the coefficient of autoregressive variable lagged at period t-1, and p is lag order of the autoregressive process, The null hypothesis for ADF was evaluated by testing whether β = 0, while the alternative hypothesis tested whether β ≠ 0. Acceptance of the null hypothesis implies that the series is non-stationary while its rejection means that the series is stationary.

2.2.2. Long-run co-integration test

According to Engle and Granger (1987), co-integration is said to exist between non-stationary variables if the residual of their long-run regression is stationary. Given this condition, all time series variables are non-stationary at level, but are co-integrated in the long-run. Therefore, following the first step of Engle -Granger approach to error correction modeling, we run the long-run co-integration regression of all the variables under study at level and test the stationarity of the regression error term. If the error term of the long – run equation is stationary at level, then it means that there is long-tern cointegration among the variable. The long-run equation in generic form is specified as:

$$AGROUTPUT = f(FIXTEL_t, ICTGIMP_t, AGRLAND_t, INTERUSE_t, AGRLAB_t, MOBCEL_t, FERTCON_t) \quad \ldots (10)$$

Specifically, the long-run regression equation in ordinary least square (OLS) form is expressed in this way:

$$AGROUTPUT = \vartheta_0 + \vartheta_1 FIXTEL_t + \vartheta_2 ICTGIMP_t + \vartheta_3 AGRLAND_t + \vartheta_4 INTERUSE_t + \vartheta_5 AGRLAB_t + \vartheta_6 MOBCEL_t + \vartheta_7 FERTCON_t + \vartheta_8 PESTIUSE_t)) + \mu_t \quad \ldots (11)$$

Where ϑ_0 stands for constant, ϑ_1, ϑ_2, ϑ_3… ϑ_8 stands for coefficient of long-run regression equation, and μ_t stands for residual of long-run cointegration.

2.2.3. Short -run error correction model

After runing the long-run regression model and established the stationarity of error term at level, the second step of Eagle-Granger approach involves estimating the short-run dynamic model using ECM technique. Application of ECM is based on the condition that all variables are stationary at first difference, that is, the order of integration of all the variables is I(1). Also incorporated in the short-run ECM equation is the lag one period of error term which is known as error correction term (ECT). Following Engle and Granger (1987), the specific estimation of the short-run dynamic relationship among the time series for this study was carried out using the ECM equation stated as:

$$\Delta AGROUTPUT = \phi_1 \Delta FIXTEL_t + \phi_2 \Delta ICTGIMP_t + \phi_3 \Delta AGRLAND_t + \phi_4 \Delta INTERUSE_t + \phi_5 \Delta AGRLAB_t + \phi_6 \Delta MOBCEL_t \phi_7 \Delta FERTCON_t + \phi_8 \Delta PESTIUSE_t) + \Upsilon \varepsilon_{t-1} + v_t \quad \ldots (12)$$

Where Δ denotes the short-run dynamic change of each variable in the model, stand for coefficients of short-run error correction model, is the ECT, ϒ is the estimated coefficient of ECT and it indicates the speed of adjustment towards long- run equilibrium. is the white noise of the short-run dynamic ECM.

3. Results and discussion

3.1 Summary statistics of variables

Summary statistics of the time series variables for this study presented in Table 1. The average value agricultural land (AGRLAND) is 668,762.90 square kilometer, and its standard deviation is 13,141.43. Agricultural output (AGROUTPUT) has an average net value of 68,317.23 million US dollar, with a standard deviation of 35,865.76. Average fertilizer consumption (FERTCON) stands at 8.82 million metric tons, with a standard deviation of 5.19. Fixed telephone subscription (FIXTEL) averages 596,627 people, with a standard deviation of 501,195.70. ICT goods import has a mean value of 4.26% of total goods import and standard deviation of 1.61. The average agricultural labour (AGRLAB) used is 42.59% of total labour employment, with 5.13 standard deviation. Mobile cellular subscription averages 87,691,802 people, with standard deviation recorded as 7,978,086. The mean pesticide used (PESTIUSE) stands at 26581.17 tons with a deviation of 19473.14. The high standard deviation observed for some variables such as FIXTEL, PESTIUSE and MOBCEL shows strong variability from rapid growth of these variables in Nigeria within the period of study (1994–2023). For instance MOBCEL rising from 18.59 million in 2005 to 172 million in 2018. The wide range (14,000–220 million) reflects this trend. Result also shows that all variables are positively skewed except AGRLAND and AGROUTPUT which are negatively skewed. Kurtosis result reflects that only FERTCON and ICTGIMP are leptokurtic (long-tailed or sharp peak) as their values exceed 3.0, while the remaining variables are platykurtic (short tailed or lower peak) as their values are below 3.0. The Jarque–Bera test of normality reveals that FERTCON and ICTGIMP are not normally distributed while the rest of the variables are normally distributed based on their probability level.

Furthermore, Figure 1 and Figure 2 present the trend patterns of variables at level and first difference respectively. From figure 1, majority of the variables reflect either upward or downward trends, with some noticeable fluctuations over time. This could probabely suggests the presence of trends or persistent shocks and it could also indicates that the mean and variance of the variables are not constant over time. This is typical of most time series variables in their ordinary level form. Conversely, Figure 2 displays the first-differenced series. The graphs appear more stable, revolving around a constant mean with relatively consistent variance over time. This could probably mean that variables are likely to be stationary at their first difference.

3.2. Results of unit root test of the time series variables

Results of unit root test are presented in Table 2. According to the result, all variables are non-stationary

Table 1: Summary statistics

	AGRLAND	AGROUTPUT	FERT CON	FIX TEL	ICT GIMP	INTER USE	AGR LAB	MOBCEL	PEST IUSE
Mean	668762.90	68317.23	8.82	596627.10	4.26	13.98	42.59	87691802	26581.17
Max.	689460.00	113644.40	22.56	1700000.0	9.49	39.20	51.26	2.20E+08	58191.67
Min.	642400.00	14039.15	4.15	96996.00	2.29	0.01	34.31	14000.00	3879.78
Std. Dev.	13141.43	35865.76	5.19	501195.70	1.61	13.34	5.13	7978086	19473.14
Skewness	-0.23	-0.40	1.41	0.85	1.44	0.47	0.27	0.27	0.52
Kurtosis	2.15	1.59	3.89	2.51	5.14	1.84	1.81	1.59	1.83
Jarque-Bera	1.09	3.05	10.18	3.65	14.95	2.62	1.99	2.66	2.86
Probability	0.58	0.22	0.001	0.16	0.001	0.27	0.37	0.26	0.24

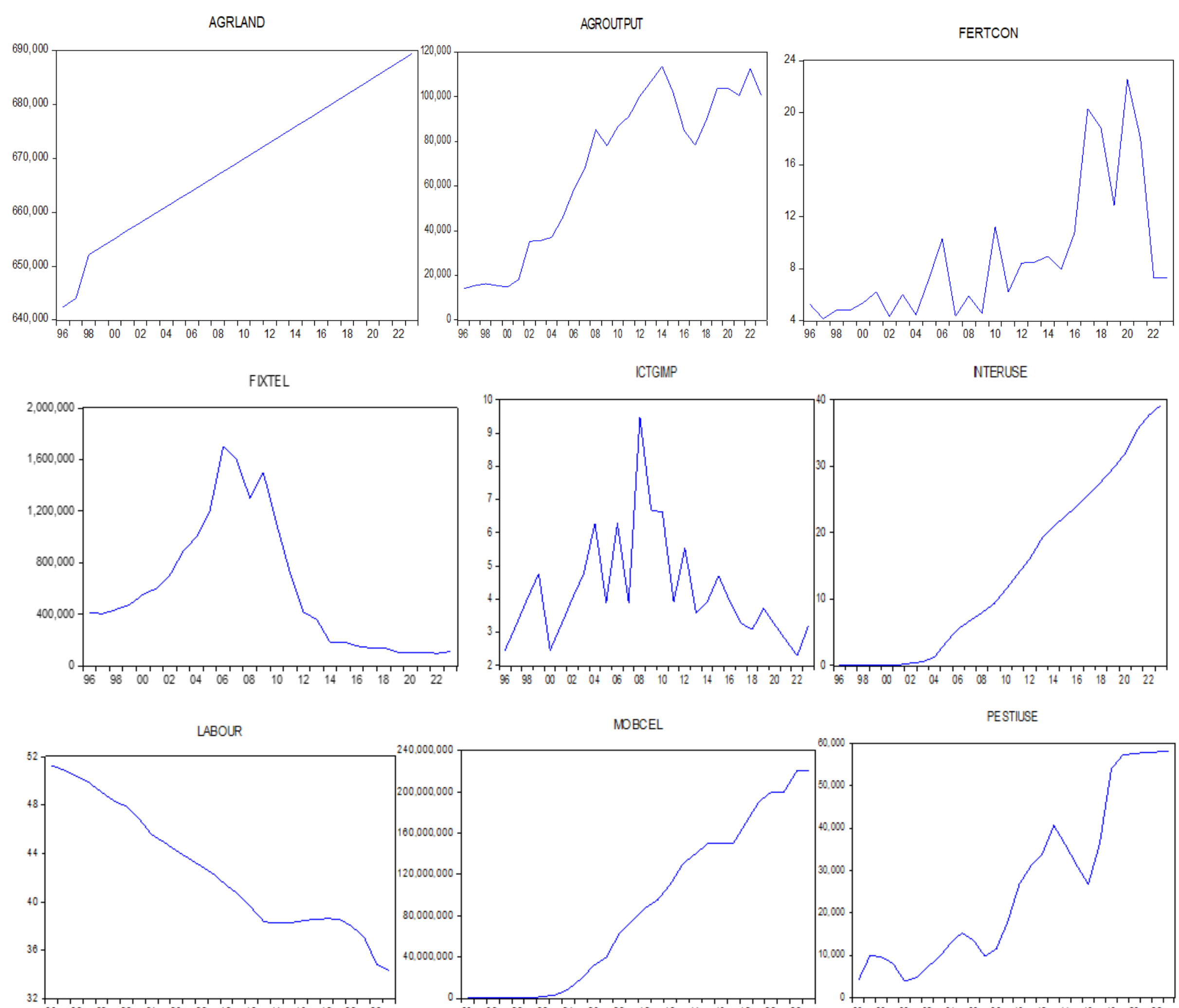

Figure 1: Presentation of multiple graphs of time series variables in level

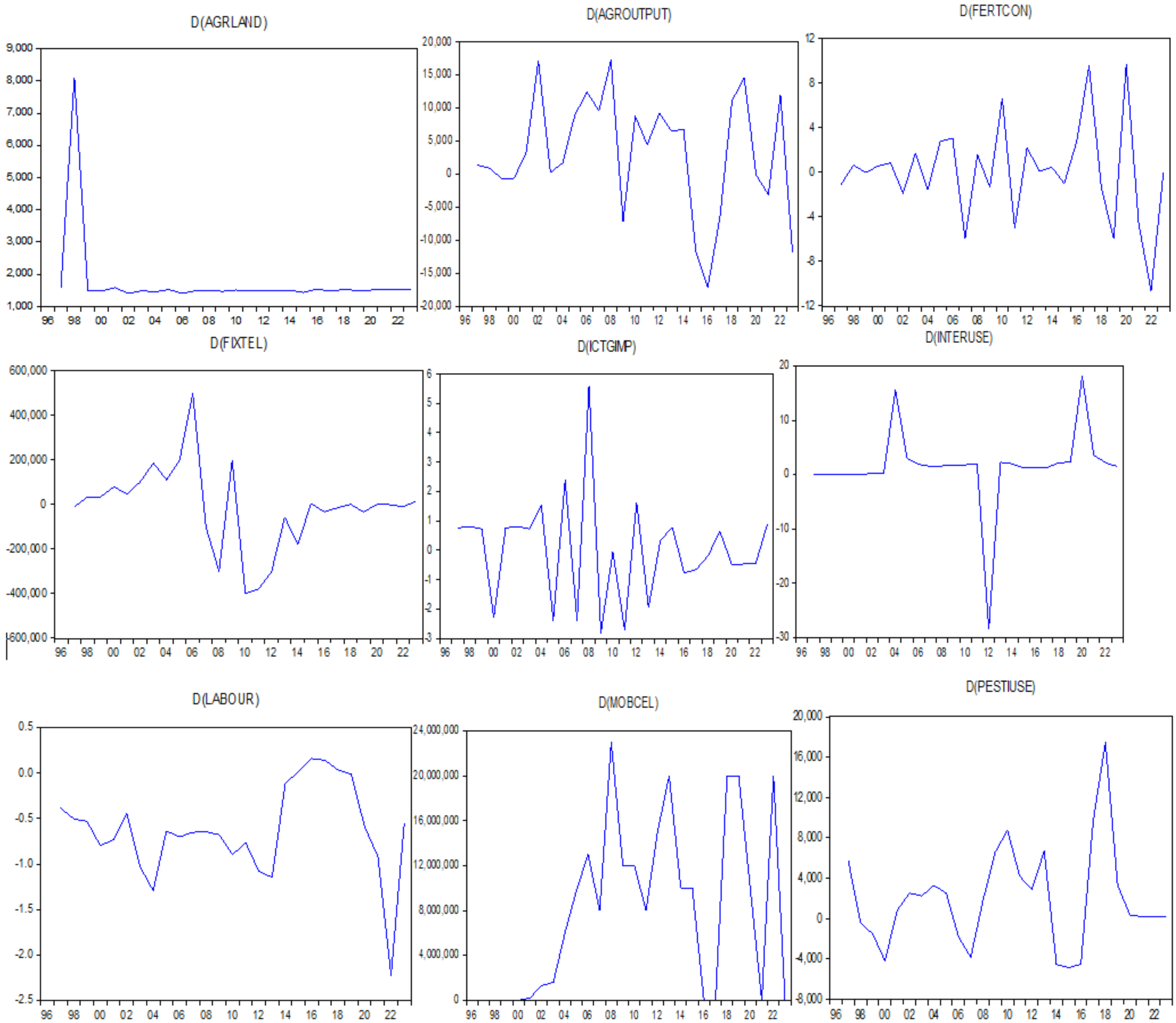

Figure 2: Presentation of multiple graphs of time series variables in first difference

at level as their calculated ADF t-statistics are lower than their corresponding 5% critical values in absolute term. However, after their first difference, all the variables become stationary as the absolute values of their respective ADF t-statistics are higher than their corresponding 5% critical values. This means that all time series variables are of integration order of one, I(1), and the use of error correction model to analyze the short-run dynamic relationship of the time series become necessary.

3.3. Long-run regression results of the influence of ICT infrastructure on agricultural output

Table 3 presents the long-run regression results of the influence of explanatory variables on total agricultural output. The results reveal that in the long-run, agricultural land, agricultural labour used, mobile cellular subscription, ICT goods import, and internet usage have significant influence on agricultural output while other variables including agricultural labour use, fixed telephone subscription, and pesticide usage have no significant effect. Specifically, coefficient of agricultural land is 0.0113 and it is significant at 1% level of probability which by implication means that an increase in agricultural land by 1% increased the agricultural output by 0.0113%. This aligns with Morante Dávila et al. (2025) who reported a positive significant influence of land on agricultural productivity in Cuispes. For labour used, the coefficient is 0.4404 and it is significant at 5%, indicating that 1% increase in labour employed for agricultural purposes results to 0.44% increase in agricultural output. The findings are

Table 2: Unit root test results of stationarity of time series

Variables	Level			1st Difference		
	5% critical value	ADF t-Statistic	Remarks	t-Stat at 5% critical value	ADF t-Statistic	Remarks
AGRLAND	-2.98104	-2.41270	Non-stationary	-2.98104	-5.0205	Stationary
AGRLAB	-0.80945	-2.98104	Non-stationary	-2.98104	-3.0241	Stationary
AGROUTPUT	-2.97626	-1.24765	Non-stationary	-3.59503	-3.9776	Stationary
FERTCON	-2.97626	-2.37003	Non-stationary	-2.98623	-5.2353	Stationary
FIXTEL	-2.97626	-0.73832	Non-stationary	-2.98104	-3.4817	Stationary
ICTGIMP	-2.98104	-1.69096	Non-stationary	-2.98104	-10.0718	Stationary
INTERUSE	-2.9763	-0.9909	Non-stationary	-2.9810	-4.8009	Stationary
MOBCEL	-2.97626	1.43363	Non-stationary	-2.98104	-3.5773	Stationary
PESTIUSE	-3.01236	2.26692	Non-stationary	-2.98623	-4.3981	Stationary

in tandem with Nwachukwu and Shisanya (2017) who reported that labour plays significant role in agricultural productivity in Kenya. ICT goods import and internet service usage are both significant at 0.01 level of sinificance with coefficients of 2.3574 and 2.5934 respectively, showing that an increment of ICT goods import and internet service usage by 1% have a resultant effect on agricultural output by 2.36% and 2.59% respectively. More so, in the long-run, mobile cellular subscription has significant effect on agricultural output at 5% and the coefficient is 0.027, implying that a unit percentage increase in mobile cellular subscription poses a positive effect on agricultural output by approximately 0.03%. This is at par with Olaniyi (2018) who made a report that internet and mobile phones collectively played significant roles in agricultural development in Africa. Assessing the fitness of the long-run model, the R-squared (R2) value is 0.9172 and it implies that about 92% variation in agricultural output is explained by the ICT infrastructure variables and other relevant variables considered for this study. The Durbin-Watson statistics is 1.891773 and it is greater than R2 value, implying that the long-run regression model is not spurious and it does not suffer from problem of autocorrelation.

3.4. Stationarity test of error term of long-run model

After estimating the long-run regression equation, we examined the stationarity of its error term. The result in Table 4 depicts that the residual of long-run regression equation is stationary at level and this implies that there is long-run co-integration among the variables, and therefore we can perform ECM analysis for short-run dynamic relationship among variables of the study.

Table 3: Long-run resgression result

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-35.3434	22.2459	-1.5887	0.1318
AGRLAND	0.0113	0.0040	2.8636	0.0097***
AGRLAB	0.4404	0.1887	2.3337	0.0307**
FERTCON	0.1807	0.7927	0.2280	0.8221
FIXTEL	-0.0152	0.0245	-0.6204	0.5418
ICTGIMP	2.3574	0.7982	2.9534	0.0069***
INTERUSE	2.5934	0.5494	4.7202	0.0001***
MOBCEL	0.0270	0.0110	2.5524	0.0195**
PESTIUSE	-0.0084	0.0134	-0.6276	0.5253
R-squared	0.9172	Durbin-Watson stat		1.891773
Adjusted R-squared	0.8921			
F-statistic	118.1027			
Prob(F-statistic)	0.00001			

*** = Significant at P ≤ 0.01 level, ** = Significant at P ≤ 0.05 level * = Significant at P ≤ 0.1 level

Table 4: Stationarity test of error term of long-run model at level

Variable	Test critical value	ADF t-Statistic	Remarks
Error term	-2.976263	-4.728831	Stationary

Table 5: Short-run error correction model result

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.2906	1.6732	1.9666	0.0648*
D(AGRLAND)	0.0118	5.2811	0.0022	0.9982
D(AGRLAB)	1.5794	0.7774	2.0316	0.0539*
D(FERTCON)	0.4392	0.1662	2.6419	0.0166**
D(FIXTEL)	-0.0353	0.0409	-0.8631	0.3995
D(ICTGIMP)	0.9961	0.3804	2.6189	0.0174**
D(INTERUSE)	0.3217	0.2687	1.1973	0.2452
D(MOBCEL)	0.1600	0.0765	2.0915	0.0429**
D(PESTIUSE)	0.0002	0.0001	1.4189	0.1806
ECT(-1)	-0.9615	0.2033	-4.7288	0.0001***
R-squared	0.810453	Durbin-Watson stat		1.486049
Adjusted R-squared	0.787321			
F-statistic	3.525938			
Prob(F-statistic)	0.012558			

*** = Significant at P ≤ 0.01 level, ** = Significant at P ≤ 0.05 level * = Significant at P ≤ 0.1 level

3.5. Short-run ECM result of the influence of ICT infrastructure on agricultural output

Table 5 presents the result of short-run error correction model. As indicated in the result, four variables, namely: agricultural labour used, fertilizer consumption, ICT goods import, and mobile cellular subscription are positively significant in influencing agricultural output in the short-run while other variables are non-significant. Precisely, agricultural land used is significant at 10% and its coefficient is 1.5794. This shows that 1% increase in land used improves the agricultural output by approximately 1.6 % in the short run, coroborating the results of previous study by Mayele et al. (2024). Fertilizer consumption, ICT goods import, and internet usage are all significant at 5% level of significance with respective coefficients of 0.4392, 0.9961, and 0.3217. This reveals that a percentatge increase in fertilizer consumption, ICT goods import, and internet usage increases the agricultural output by 0.44%, 0.99%, and 0.32% respectively in the short-run. The result is in tandem with Matsvai and Hosu (2024) who reported that the use of internet service had positive significant impact on agricultural development in South Africa. The error correction term(ECT) is -0.9615 and it is significant at 1%. This implies that the speed of adjustment towards the long run equilibrium is 96.15%. Since the study made use of annual data , -0.9615 ECT cofficient also implies that almost the 96.15%. discripancy between the long-run equilibrium and short-run dynamic is corrected within one year.

3.6. Results of post-estimation diagonistic test

The post estimation diagonistic test for ECM is presented in Table 6. The test for serial correlation, heteroskedasticity and normality were carried out using Breusch-Godfrey serial correlation LM test, Breusch-Pagan-Godfrey heteroskedasticity test, and Jarque-Bera statistic for normality test respectively. Based on the F-statistics and the corresponding p-value in Table 6, we uphold the null-hypothses that no serial correlation among the variables, that residuals are homoscedastic and normally distributed as the p-values of serial correlation test (p = 0.296), heteroskedasticity test (p = 0.734), and normality test (p = 0.879) are not significant. This implies that the model is statistically reliable to use for econometric analysis of this study.

4. Conclusion and recommendations

Based on the findings of this study, it can be concluded that the adoption of some of ICT infrastructure such as mobile cellular, internet facility and ICT import

Table 6: Post estimation diagnostic test of error correction model

Diagnostic Indicator	F-Statistics	P-value	H_0 (Null-Hypothesis)
Breusch-Godfrey Serial Correlation LM Test	1.3162	0.2957	No serial correlation among the variables
Breusch-Pagan-Godfrey Heteroskedasticity Test	0.6413	0.7338	Residuals are homoskedastic
Jarque-Bera statistic for Normality Test	0.2581	0.8789	Residuals are normally distributed

goods have significant impact on agricultural output in Nigeria either in the long-run or short-run. Therefore, efforts should be made to expand mobile network coverage in agrarian communities to enhance timely communication and access to agricultural information. Government policies should aim at improving internet access in rural communities by investing in broadband infrastructure and reducing the cost of data services for rural farmers. Policy makers should ease restrictions of ICT goods import and provide enabling conditions for the importation of essential agricultural related ICT equipment such as drones, GPS devices, and processing tools. Lastly. there should be incorporation of ICT strategies in national and regional agricultural plans by Nigerian government.

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