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Information and Communication Technologies and Agricultural Production: New Evidence from Africa

Robert Ugochukwu Onyeneke [1], Daniel Adu Ankrah [2], Richmond Atta-Ankomah [3], Fred Fosu Agyarko [4], Chinenye Judith Onyeneke [5] and Jalil Ghassemi Nejad [6,*]

1. Department of Agriculture, Alex Ekwueme Federal University Ndufu-Alike, Ikwo 482131, Nigeria
2. Department of Agricultural Extension, University of Ghana, Accra P.O. Box LG 68, Ghana
3. Institute of Statistical Social and Economic Research (ISSER), College of Humanities, University of Ghana, Accra P.O. Box LG 74, Ghana
4. Institute for Scientific and Technological Information (INSTI), Accra P.O. Box M 32, Ghana
5. Centre for Entrepreneurship and Employability, Alex Ekwueme Federal University Ndufu-Alike, Ikwo 482131, Nigeria
6. Department of Animal Science and Technology, Sanghuh College of Animal Life Sciences, Konkuk University, Seoul 05029, Republic of Korea

* Correspondence: jalilgh@konkuk.ac.kr

Abstract: While information and communication technologies (ICT) have proven to be useful in boosting agricultural production and productivity, regardless of the geographical location, much of the discussion on ICT and their impact focus on the global north, with deficient literature on the global south. The limited account of the global south shows mixed conclusions on the impact of information and communication technologies on agricultural production, with most studies focusing on crop production, as a proxy for agricultural production, leaving out livestock production. Animated by this concern, this article explores the impact of ICTs on agricultural production (crop and livestock) in Africa using panel data from 32 African countries and the panel autoregressive distributed lag model as the estimation technique. We find that individuals using internet significantly increased crop production in the long run. Specifically, a percentage increase in internet patronage increases crop production by 0.071% but significantly decreases the livestock production index, both in the short and long run. Mobile phone subscriptions had a significant negative impact on crop production in the long run but had a significant positive impact on livestock production in the long run. Fixed phone subscriptions significantly increased crop production in the long run but significantly decreased livestock production index in the long run. The findings show bidirectional causality between crop production and internet patronage, livestock production and individuals using internet, crop production and mobile cellular subscription, crop production and net national income, and rural population and both crop and livestock production. We recommend that governments in Africa increase funding investment in digital technologies to foster increased agricultural production while addressing structural challenges that constrain increased access to digital agricultural technologies. It might be useful if governments in sub-Saharan Africa (SSA) incentivize the telecommunication companies to extend digital coverage to rural areas through tax rebates and holidays to encourage rural inclusion in the digital space to bridge the digital divide.

Keywords: individuals using the internet; mobile phone subscriptions; fixed telephone subscriptions; net national income per capita; credit to the private sector; rural population; crop production; livestock production; panel ARDL

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1. Introduction

Africa lags significantly behind the global north in terms of the use of ICT and other digital technologies in business activities, including agriculture, owing to the substantial financial investment and expertise required for providing digital technological services.

While a large number of people now are hooked to the internet, fixed telephone, and mobile phones in most developed countries compared to a couple of decades ago, the use of digital technologies, however, is relatively less pronounced in Africa, particularly in agriculture [1]. Estimates by Kuduma et al. [1], for example, indicate that only 13% of smallholder farmers in sub-Saharan Africa have access to various digital technologies. Indeed, internet penetration rate in sub-Saharan African countries has remained low. In sub-Saharan Africa, the internet penetration (individuals using the internet) was 16% in 2015 and rose to 29% of the population as of 2020 [2].

There is an uneven adoption of information and communication technologies by scale and geography within Africa. For instance, mobile money services dominate (85%) in Kenya, with presence among more than half (55%) of the population in Ghana, less than half (45%) in Tanzania, and relatively low (8%) in South Africa and Nigeria (4%) [1]. As of 2021, there were 515 million mobile services subscribers in sub-Saharan Africa, representing about 46 percent of the population [3]. Recent estimates show that 40% of the adult population is connected to mobile internet, whereas 44% of individuals live in areas with mobile network coverage, but they do not use mobile internet services [3]. Notwithstanding the uneven coverage, a positive effect has been established between mobile money services and financial inclusion, welfare, and other development outcomes in sub-Saharan Africa (SSA) [4–7].

Meanwhile, significant advances in the use of technology in agriculture in developed economies have occurred in the last two–three decades, culminating in the birth of what is termed "precision agriculture", which involves machine software and sensors as well as more contemporary agricultural technologies, such as drones, robots, and farm management software. This development has occasioned the emergence of terminologies such as digital farming [8], smart farming [9,10], agriculture 4.0 [11,12], and Farming 4.0 [13,14]. Technological advances have led to substantial improvements and scaling up of innovations driven by terminologies such as the internet of things (IoT), cloud, artificial intelligence (AI), gene editing, and big data in consolidating the fourth agricultural revolution [15,16]. Agriculture 4.0 involves the adoption of digital technologies in managing agricultural production and processes [17,18] in monitoring production variables of interest [19] contingent on the scientific dataset [12,20–22]. The data shape and guide food crop cultivation and animal rearing up to processing [23,24], reducing production costs and minimizing wastage by only using essential inputs [25,26]. Gacar et al. [27] argued that digital technologies promote sustainable agriculture. Agriculture 4.0 includes the use of information and communication technologies (including big data, IoT—internet of things, GPS—geographical positioning systems) on farmers' farms to improve efficiency and productivity [12,15,28,29]. Agriculture 4.0 steps in to effectively address the uncertainties in the agricultural value chain [12,30].

More recently, the exigencies of the COVID-19 pandemic have made more apparent the critical role of ICT in agricultural development and, hence, the need to ramp up use of ICT in agricultural production in SSA and reap the potential benefits thereof. The existing literature suggests that ICT facilitate information sharing including agricultural extension and advisory services in emerging and developed economies, helping to reduce information asymmetries and transaction costs [31–33]. Moreover, in the face of climate variability and change, ICT significantly improve agricultural production, food security, profitability, and sustainable agriculture [34].

Despite the apparent benefits of ICT, there is a lack of clarity on how information and communication technologies have improved the welfare outcomes of smallholder farmers in SSA. For instance, Goedde et al. [35], Harkin [36], and May et al. [37] indicated that ICT and other digital technologies have only 30% of active users in SSA. The low deployment or usage of ICT in agriculture in SSA is largely as a result of structural challenges and infrastructural deficit (e.g., limited and differential access to electricity, mobile networks, internet, fixed phone subscriptions, and access to technologies) that have persisted for several years [1,34,38,39]. Other impediments using ICT and other digital technologies in

SSA include language barriers, inappropriate policies, high cost of technology, accessibility, socio-cultural factors, poor governing framework, low electronic literacy, and low digital skills [34]. Moreover, rural areas remain less endowed in the digital ecosystems relative to the urban areas [34,40]. In the context of these challenges, mobile phones have emerged as the main tool for reducing the digital divide in Africa, helping to reduce post-harvest losses, price volatility, save time and cost in agricultural extension delivery, and provide timely information on prices, weather, financial service, and so on and so forth [41–43].

This article examines the research question of: What remains the impact of information and communication technologies on agricultural production? This topic has received much attention from researchers, particularly in the global north [44–47]. Despite the existing body of knowledge, the estimation of the impact of information and communication technologies using proxies, such as mobile phone subscriptions, fixed telephone subscriptions, and individuals using internet; and covariates, such as net national income per capita and credit to the private sector covering SSA, have received less attention. The impact of information and communication technologies on economic development and agricultural production appears skewed towards the global north and Asia, with scarce evidence on SSA [48], until recently [43]. For instance, studies [44,45] have explored the impact of internet use on economic welfare in China. Li et al. [44] examined the ramifications of internet use on good agricultural practices (GAP). Specifically, few program-specific and country studies have examined the digital technology and agricultural production nexus in Africa. Consequently, the literature [49–54] is scarce on the impact of information and communication technologies on agricultural transformation. This motivated our interest to explore the impacts of information and communication technologies on agricultural production, including livestock production, which has been neglected in the ICT–agriculture nexus literature.

The existing empirical literature on the impact of information and communication technologies on agriculture in Africa is mostly based on micro data at either national or subnational levels. Recent attempts to study the issue at the continental or cross-country level include Nguimkeu and Okou [55] and Oyelami et al. [56]. While Nguimkeu and Okou [55] broadly focused on the informal sector, Oyelami et al. [56] examined the impact of ICTs on the agricultural sector performance in SSA using the panel autoregressive distributed lag (ARDL) approach. This article makes three main contributions to the literature on information and communication technologies agricultural production nexus. First, our study extends beyond Oyelami et al. [56] to include additional independent variables, such as net national income per capita; credit to private sector; and the rural population. Second, our study is more holistic in examining the effect of information and communication technologies on agricultural production. Recent attempts have examined the impact of information and communication technologies on agriculture in terms of the environmental, social, and economic outcomes, particularly relating to changes in farmers' identities, values, and practices [57,58]. We capture agricultural production to include both crops and livestock, which remain sparing in the extant literature, and also departure from Oyelami et al. [56], which captured agricultural performance using value added. Finally, we contribute to the estimation rigor using panel autoregressive distributed lag (ARDL) to estimate the short- and long-run effects of information and communication technologies on agricultural production, including the direction of causality with important policy implications for Africa.

The objective of our paper, therefore, is to explore the impact of information and communication technologies on agricultural production in Africa. Our study is novel because it considered the impacts of information and communication on both crop and livestock production in Africa using other covariates, such as rural population, per capita income, and credit to the private sector. There is a dearth of empirical evidence on the impact of ICTs on livestock and crop production with an African scope.

The rest of this article is organized as follows. Section 2 reviews the relevant literature pertinent to the study, while Section 3 deals with the methodology. Section 4 presents the results, including the discussions, Section 5 concludes with policy implications and recommendations, and the last section presents the limitations and future research direction.

2. Review of Empirical Literature

Empirical quantitative research on the effect of information and communication technologies on agricultural production in Africa has been conducted from two main methodological approaches. The first approach involves cross-country analysis, often using cross-country panel data (e.g., [56,59,60]), while the other usually involves country-specific or sub-country level studies using micro-level data (e.g., [61,62]). A strand of the literature using the latter approach has sought to understand or describe the channels by which information and communication technologies affect agricultural production and value chains, characterize the stakeholders or actors driving this effect, as well as the factors shaping the adoption and use of information and communication technologies in agriculture (e.g., [41,63–65]). Generally, the quantitative evidence, particularly that using cross-country data, is more scant, especially in Africa. This section presents a brief review of the existing literature to help contextualize the key objectives of this study, as well as its contribution to the scholarly literature.

The empirical evidence based on the analysis of cross-country panel data in Africa suggests that information and communication technologies have a significant effect on agricultural production (see, for example, [59,66]). Dagne and Oguamanam [67] assessed the impact of ICTs on agricultural production using qualitative data. They found that ICTs link small-scale producers to the markets. Ali et al. [66] assessed whether specific ICTs have a significant impact on agricultural production. This study showed that ICT had a positive but insignificant effect on net profit per acre [66]. It should be noted that the years after Ali et al.'s study have seen the advent and growing penetration of many mobile-phone-based digital innovations, such as mobile money, 3G/4G internet services, and other mobile phone applications that could positively influence the relationship between the use of mobile phone and agricultural production in many significant ways (see [68,69]). Ali et al. [66] found additionally that the impact of ICTs, seed, fertilizer and credit significantly increased agricultural productivity in Zambia. Unlike Ali et al. [66], a later study by Evans [59], which also used panel data of African countries, showed that both mobile phones and internet play significant roles in agricultural development in Africa. Evans [59] further showed nonlinear effects where mobile phone penetration has an increasing positive effect on agricultural value added, while internet usage has a U-shape effect on agricultural value added. It is important to note that the study by Evans [59] covered 44 African countries over a period of 15 years, from 2001 to 2015, as well as using system Generalized Method of Moments (GMM) estimator, and these factors could account for different results on mobile phones.

A more recent study by Oyelami et al. [56] focused on the effect of ICT infrastructure on agricultural sector performance in sub-Saharan Africa, using agricultural value added and agriculture products as a percentage of total merchandise export as the measures of performance. While findings by Oyelami et al. [56] are qualitatively similar to the key findings by Evans [59], their study presents additional important insights, particularly through the use of analytical models that help to delineate the long-run and short-run effects. With data covering 23 years (1995–2017) from 39 countries and employing panel autoregressive distributed lag (ARDL) approach, where mobile cellular telephone subscription and individual using internet were the key independent variables, Oyelami et al. [56] found that ICT infrastructure has a positive effect on agricultural sector performance in the long run but the same cannot be said of the short run. An equally recent study by Suroso et al. [60], which specifically focused on the effect of internet on agricultural sector performance and used panel data of 126 countries, including 32 countries from Africa, covering a period of eight years (2012–2019), showed that internet users, fixed broadband subscriptions, and secure internet servers have a significant and positive effect on agricultural sector performance. However, further heterogeneity analysis by Suroso et al. [60]

showed that this effect only pertains to countries from Africa, Asia, and Oceania, as well as economies classified as emerging and developing.

In Africa, where agriculture is dominated by smallholder farmers, much of the micro-level empirical evidence on the effect of information and communication technologies on agricultural production has centered on smallholder farming. For example, based on data from 200 smallholder farmers in Northern Nigeria, Sennuga et al. [62] found that short message services (SMS text reminders) to the farmers had a positive and significant effect on the agricultural productivity of the farmers. Similarly, Quandt et al. [61] examined the relationship between mobile phone use and agricultural yield using data from 179 farmers in four rural communities in Tanzania. Their results showed a positive association between mobile phone use for agricultural activities and reported maize yields, with many of the farmers also reporting increases in agricultural profits. A previous study by Kabbiri et al. [64], which used an extended version of the technology acceptance model and with data from 300 dairy farmers in Uganda analyzed using structural equation modeling, however, showed that the use of mobile phones by farmers is mainly limited to normal communication and that perceived ease of use of mobile phones is important for mobile phone adoption among the farmers studied.

While some of the empirical micro-level evidence point to the important effect of information and communication technologies, particularly mobile phones or mobile-phone-based technology, on agricultural production, others have focused on what farmers with mobile phones use them for in agricultural production activities [63,65,70]. Masuka et al. [70], for example, studied 131 farmers in Marondera district of Mashonaland East province in Zimbabwe and showed that they use their mobile phones for accessing advisory services, accessing market information on inputs and produce, weather data, and for mobile phone money transfers for transaction and crop insurance. Masuka et al. [70] argued that, through the use of mobile phones, the farmers were able to make informed decisions and saved time and transport cost. Ogbiede & Ele [65] investigated how farmers have applied mobile phone technology with data from 328 smallholder farmers in Cross River State of Nigeria. The main findings by Ogbiede & Ele [65] indicated that mobile phone use was most common among younger farmers with at least secondary education who mainly use mobile phones for seeking market information. Mainly focusing on the youth, Irungu et al. [63] explored ICT application in agriculture in Kenya and described various ICT-enabled avenues, including social media handles, voice messages, and SMS, used by the youth to obtain production technologies, sharing production information, and money transactions.

Outside of Africa, and particularly in other developing contexts, evidence on the effect of ICT on agriculture through micro studies has begun to emerge. Khan et al. [71] evaluated the impact of mobile phone and internet usage on the selection of sales productivity and marketing channels among 580 wheat growers from four districts in the Khyber Pakhtunkhwa Province (KPK) of Pakistan. By applying propensity score matching and Heckman's two-step regression techniques, Khan et al. [71] found that mobile phone and internet usage significantly improved the efficiency of selecting sales channels, increasing agricultural profits and, consequently, positively affecting rural farmers' income. Similarly, an earlier study by Khan et al. [72] using a national dataset of 7987 rural households in Afghanistan found that mobile phone usage and mobile phone promotion policy reduced inorganic fertilizer application among the farmers, helping to ensure environmental and agricultural sustainability goals. In rural Viet Nam, Kaila & Tarp [73] found through a panel dataset (from 2008 to 2012) that internet access is associated with a 6.8% increase in total agricultural output as a result of more efficient use of fertilizer, particularly among younger households and in the less developed northern provinces of Viet Nam.

Ma et al. [45] established that internet use meaningfully increased rural households' income and expenditure in China. Zheng et al. [46] found that using the internet positively impacts the technical efficiency of farmers producing banana in China. Jensen [42] showed that mobile phones significantly impacted on post-harvest losses, profit, and price volatility among fishermen in Kerala in India.

In summary, we observed a paucity of information using cross-country data covering sub-Saharan African countries that illuminate the impact of information and communication technologies on agricultural production. Rather, silos of studies that use country-specific cases dominate. There is, therefore, the need to have more cross-country studies to bridge the unbalanced literature, particularly with policy implications for the global south. Studies on information and communication technologies have overly concentrated on mobile phones and internet, with limited consideration of the vast array of ICTs (radio, television, computers, smartphones, and tablets). Conspicuously missing in most of the literature is the consideration of variables such as net national income per capita; credit to the private sector; rural population; and its impact on agricultural production (crop and livestock production) using rigorous estimation approaches such as the panel autoregressive distributed lag model (ARDL). Our study seeks to fill the lacuna in the literature.

3. Methodology

3.1. Data Source

This paper focused on the African continent, where access to information and communication technologies is still low. We used data from 32 countries in Africa (see Table 1 for details).

Table 1. List of countries studied.

S/No	Country
1	Algeria
2	Angola
3	Benin
4	Botswana
5	Burkina Faso
6	Burundi
7	Cape Verde
8	Cameroon
9	Chad
10	Congo Democratic Republic
11	Côte d'Ivoire
12	Djibouti
13	Egypt
14	Gabon
15	Ghana
16	Kenya
17	Lesotho
18	Mali
19	Mauritania
20	Mauritius
21	Morocco
22	Mozambique
23	Namibia
24	Nigeria
25	Sao Tome and Principe
26	Senegal
27	South Africa
28	Tanzania
29	Togo
30	Tunisia
31	Uganda
32	Zambia

Table 2 presents the description of variables and data source.

Table 2. Description of variables and data source.

Variables	Source
Crop production index (2014–2016 = 100)	World Development Indicators of World Bank
Fixed telephone subscriptions (number of persons)	World Development Indicators of World Bank
Livestock production index (2014–2016 = 100)	World Development Indicators of World Bank
Individuals using the internet (% of population)	World Development Indicators of World Bank
Mobile cellular subscriptions (number of persons)	World Development Indicators of World Bank
Adjusted net national income per capita (current US$)	World Development Indicators of World Bank
Domestic credit to private sector by banks (% of GDP)	World Development Indicators of World Bank
Rural population (% of population)	World Development Indicators of World Bank

Link to the data: https://databank.worldbank.org/source/world-development-indicators#. Accessed 22 October 2022.

Each variable has 512 values, i.e., 32 countries multiplied by 16 years.

3.2. Analytical Technique

The paper applied the panel autoregressive distributed lag (ARDL) framework to estimate the relationship between information and communication technologies and agricultural production (proxied by crop production index and livestock production index) in Africa and used STATA 17 software for the analysis, as applied by Chidiebere-Mark et al. [74] and Emenekwe et al. [75] in their studies in Africa. One important feature of the panel ARDL framework is ability to determine long-run relationships between the dependent and independent variables and being free from the endogenous problem [76]. The Pesaran Cross-sectional Augmented Dickey–Fuller (CADF) and Im–Pesaran–Shin unit-root test were used to determine the existence of unit roots among the variables, while the Pedroni test and Westerlund test were applied to test whether the variables are cointegrated. The panel autoregressive distributed lag was used to compute the long- and short-run impacts of the independent variables on the dependent variable.

The implicit model of our panel autoregressive distributed lag framework is stated as follows:

$$Yk = f(X1, X2, X3, X4, X5, X6, e) \tag{1}$$

where:

Yk = agricultural production;
$X1$ = individuals using the internet (% of population);
$X2$ = mobile cellular subscriptions (number of persons);
$X3$ = fixed telephone subscriptions (number of persons);
$X4$ = adjusted net national income per capita (current USD)
$X5$ = domestic credit to private sector by banks (% of GDP);
$X6$ = rural population (% of total population);
e = error term;
k = 1 (crop production index), 2 (livestock production index).

To control for possible heteroskedasticity in our dataset, we converted the real values of the variables to their logarithmic values. The panel autoregressive distributed lag model with the logarithms is presented thus:

$$\ln Y_{it} = \beta_0 + \beta_1 \ln X1_{it} + \beta_2 \ln X2_{it} + \beta_3 \ln X3_{it} + \beta_4 \ln X4_{it} + \beta_5 \ln X5_{it} + \beta_6 \ln X6_{it} + \varepsilon_{it} \tag{2}$$

where i: 1, 2, 3, ..., 32 countries; t: 2004, 2005, 2006, ..., 2019 year; ln denotes natural logarithm; and ε is the error term. Furthermore, β_1, β_2, β_3, β_4, β_5, and β_6 define the estimated percentage change in agricultural production (crop production index and livestock production index) caused by a one percent change in internet use, mobile cellular subscriptions, fixed telephone subscriptions, net national income, credit to the private sector, and rural population, respectively, while all other factors are constant.

Standard panel regressions as the expressed model in Equation (2) can be used to estimate efficiently and consistently if all the variables are stationary at levels. In a situation where some variables are stationary at levels and others stationary at first difference, a dynamic model for panel data with cointegration is required, such as the Pooled Mean Group (PMG) and Dynamic Fixed Effect (DFE) models. To understand the long-run impacts and the long-run adjustment rate, it is necessary to identify each country's short-run dynamics. The long- and short-run effects of ICTs and covariates (such as net national income, domestic credit to the private sector, and rural population) on crop production index over time and across different African countries using the panel ARDL can be estimated thus:

$$\begin{aligned}\Delta \ln Y_{it} = {} & \beta_i + \beta_{1i} \ln X1_{i,t-1} + \beta_{2i} \ln X2_{i,t-1} + \beta_{3i} \ln X3_{i,t-1} + \textstyle\sum_{j=1}^{p_1} \gamma_{1ij} \Delta \ln Y_{i,t-j} + \sum_{j=1}^{p_2} \gamma_{2ij} \Delta \ln X1_{i,t-j} \\ & + \textstyle\sum_{j=1}^{p_3} \gamma_{3ij} \Delta \ln X2_{i,t-j} + \sum_{j=1}^{p_4} \gamma_{4ij} \Delta \ln X3_{i,t-j} + \sum_{j=1}^{p_5} \gamma_{2ij} \Delta \ln X4_{i,t-j} + \sum_{j=1}^{p_6} \gamma_{3ij} \Delta \ln X6_{i,t-j} \\ & + \textstyle\sum_{j=1}^{p_7} \gamma_{4ij} \Delta \ln X6_{i,t-j} + \epsilon_{it}\end{aligned} \tag{3}$$

where Δ denotes first differences, β_i is a constant, $\gamma_{nij(n=1,\ldots,7)}$ denote short-run coefficients, $\beta_{mi(m=1,\ldots,6)}$ are long-run coefficients, and ϵ_{it} is an error term. Equation (3) could be restated with an error correction term as follows:

$$\begin{aligned}\Delta \ln Y_{it} = {} & \vartheta_i + \textstyle\sum_{j=1}^{p_1} \gamma_{1ij} \Delta \ln Y_{i,t-j} + \sum_{j=1}^{p_2} \gamma_{2ij} \Delta \ln X1_{i,t-j} + \sum_{j=1}^{p_3} \gamma_{3ij} \Delta \ln X2_{i,t-j} + \sum_{j=1}^{p_4} \gamma_{4ij} \Delta \ln X3_{i,t-j} \\ & + \textstyle\sum_{j=1}^{p_5} \gamma_{5ij} \Delta \ln X4_{i,t-j} + \sum_{j=1}^{p_6} \gamma_{6ij} \Delta \ln X5_{i,t-j} + \sum_{j=1}^{p_7} \gamma_{7ij} \Delta \ln X6_{i,t-j} + \lambda_i ECT_{i,t-1} + \epsilon_{it}\end{aligned} \tag{4}$$

where $ECT_{i,t-1}$ is the error correction term.

The paper applied the Dumitrescu and Hurlin [77] panel causality test to determine causality among variables. The model of the Granger causality is written:

$$y_{it} = \alpha_i + \sum_{j-1}^{J} \lambda_i^j y_{i(t-j)} + \sum_{j=1}^{J} \beta_i^j x_{i(t-j)} + \mu_{it} \tag{5}$$

where y and x are the observables. λ_i^j denotes the panel autoregressive parameters, while β_i^j denotes the regression coefficient estimates, and both are assumed to vary across cross-sections. The null and alternative hypotheses are stated as follows:

$$H_o : \forall j : \beta_i^j = 0 \; H_o : \forall j : \beta_i^j \neq 0 \tag{6}$$

4. Results and Discussion

4.1. Summary Statistics

Table 3 presents the descriptive statistics of the variables used in the analyses. On average, 769,139 individuals are subscribed to fixed telephones in the 32 African countries. With regards to the crop production index, the minimum recorded throughout the period under study (2004–2019) for the aforementioned African countries is approximately 40, whereas the maximum production is approximately 172. Moreover, the average livestock production index recorded for these countries is approximately 94. We observed an uneven patronage of internet across countries, with some countries being very high, whilst other remained very low. Thus, one country among the 32 African countries recorded high 74.4% (maximum) internet patronage, whereas another recorded less than 1% (i.e., 0.20%) of its populace using the internet. On average, internet patronage stands at 16.3%, as shown in Table 3. This gives a clear indication of the low subscription to the internet in the majority of the African countries.

Although the maximum adjusted net income per capita recorded from our summary statistics is USD 11,114.26, most of the countries studied belong to the low-income economy. From the description given by the World Bank of the gross national income per capita, a country whose gross national income per capita is less than USD 4255.00 falls under the low-income or lower-middle-income category [78]. Hence, the average adjusted net income per capita (USD 1915.03) and the median (USD 1151.36) reported in the summary statistics table indicate that most of the countries under study fall in the low-income or lower-middle-income category [79].

Table 3. Descriptive statistics (N = 512).

Variables	Median	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
Fixed telephone subscriptions	138,584.00	0.00	11,852,539.00	769,139.15	1,783,668.60	3.645	14.582
Crop production index (2014–2016 = 100)	94.67	40.18	172.26	92.0869	19.62481	−0.005	0.907
Livestock production index (2014–2016 = 100)	96.32	49.48	134.54	93.9289	14.98644	−0.163	0.568
Individuals using the internet (% of population)	9.15	0.20	74.38	16.29	17.11	1.252	0.608
Mobile cellular subscriptions	6,450,319.50	7745.00	184,592,255.00	16,729,760.59	26,294,996.51	3.042	11.313
Adjusted net national income per capita (current USD)	1151.36	65.07	11,114.26	1915.03	1842.35	1.857	4.121
Domestic credit to private sector by banks (% of GDP)	18.91	1.07	106.26	25.89	20.00	1.501	1.856
Rural population (% of total population)	56.02	10.26	90.86	53.71	17.66	−0.165	−0.501

As it is widely acknowledged, the private sector is one of the most important sectors that drive the economic growth of every country [79]. Per the results in Table 3, the maximum domestic credit given to the private sector by banks in the countries studied is 106.3%, whilst the lowest domestic credit given to the private sector by local banks is approximately 1.1%. On average, domestic credit given to the private sector by banks in these 32 African countries is approximately 25.9%, while the median is 18.91%.

We observed that the maximum rural population recorded in the summary statistics results is 90.86%, whilst the minimum recorded is 10.26%. The average rural population of the studied countries is 53.71%, while the standard deviation is 17.66%.

4.2. Trend of the Dependent and Independent Variables

Figure 1 presents the trend of crop production index across the 32 different African countries from 2004 to 2019. We observe that most of the countries had an upward trend in the crop production index. Whilst some countries had a fairly stable trend, others had a downward trend. Specifically, Mauritius has been witnessing a decline in its crop production index since the year 2004. There has been a slow rise since 2017. Moreover, countries such as Namibia, Sao Tome and Principle, and Nigeria have seen a fairly flat/stable crop production for almost two decades now. Cabo Verde had a stable trend from 2004 to 2013 and, since then, has had a negative slope (i.e., it has been experiencing a downward trend since 2013). South Africa shows an interesting pattern, where the country experienced a fairly stable rate in the crop production index from 2004 to 2013 and had experienced a steep decline from 2013 to 2015. It also had a steep rise from 2015 to 2017 and has taken a steep decline to 2019.

Figure 2 also presents the trend of livestock production index across different African countries from 2004 to 2019. The figure generally depicts a mixture of all trends. Countries such as Congo Democratic Republic, Nigeria, Gabon, and Egypt exhibited a fairly stable trend, whereas Chad, Angola, Ghana, and Togo saw an upward trend in their livestock production index. Countries such as Senegal, Tanzania, and Morocco had also seen an upward trend in their livestock production index. Botswana, Djibouti, and Mali also had an undulating trend.

Figure 1. Trend of crop production index across different African countries from 2004 to 2019.

Figure 2. Trend of livestock production index across different African countries from 2004 to 2019.

Regarding the trend of fixed telephone subscriptions as shown in Figure 3, we observe that most of the countries have had a stable trend since 2004. In addition to the stable trends in these countries, it can be seen clearly that the subscriptions are very low. Interestingly, it is only Algeria that recorded an upward trend in fixed telephone subscriptions. Although Egypt exhibited an undulating trend, it is the country that had the highest fixed telephone subscriptions among the 32 African countries under study.

Figure 3. Trend of fixed telephone subscriptions across different African countries from 2004 to 2019.

The trend of individuals using the internet across the different African countries from 2004 to 2019 exhibited in Figure 4 shows a positive slope. Thus, almost all the countries under study have been increasing their internet patronage since the year 2000. It can be noticed that Burundi and Chad exhibited a fairly stable trend in their internet patronage. Although they are stable, their stability is at the very bottom of the graph (i.e., they have very low internet patronage). Regarding the countries with the upward trends, they have exhibited high internet patronage with time.

Figure 4. Trend of individuals using the internet across different African countries from 2004 to 2019.

Regarding the trend of mobile cellular subscription as shown in Figure 5, a majority of the countries had a fairly stable trend, with the exception of countries such as Ghana, Nigeria, Tanzania, South Africa, and Egypt. These countries (i.e., Ghana, Nigeria, Tanzania, South Africa, and Egypt) recorded an upward trend in mobile cellular subscriptions. It can be seen clearly from Figure 5 that Nigeria has the highest number of mobile cellular subscriptions among the countries under study.

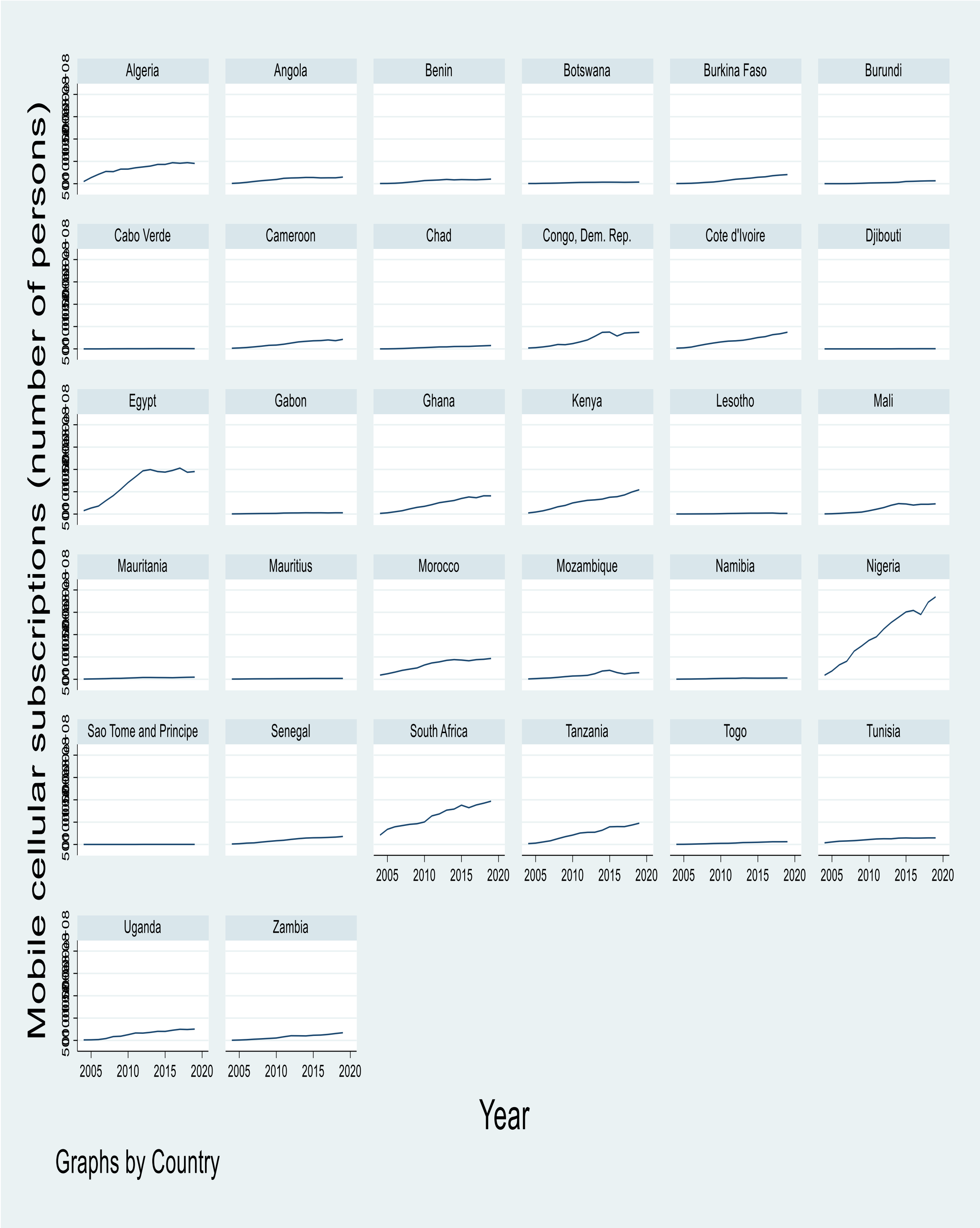

Figure 5. Trend of mobile cellular subscriptions across different African countries from 2004 to 2019.

The rural population trend in Figure 6 shows that most of the countries exhibit a decreasing trend in percentage of the population living in rural Africa. It can be noticed that all the countries studied exhibit a decreasing trend in rural population, with the lines in the graphs sloping downwards. This may be an indication of increasing urbanization fueled by migration to urban areas in Africa. Burkina Faso, Burundi, Chad, Tanzania, and Uganda had the highest percentage of their population living in rural areas among the countries studied.

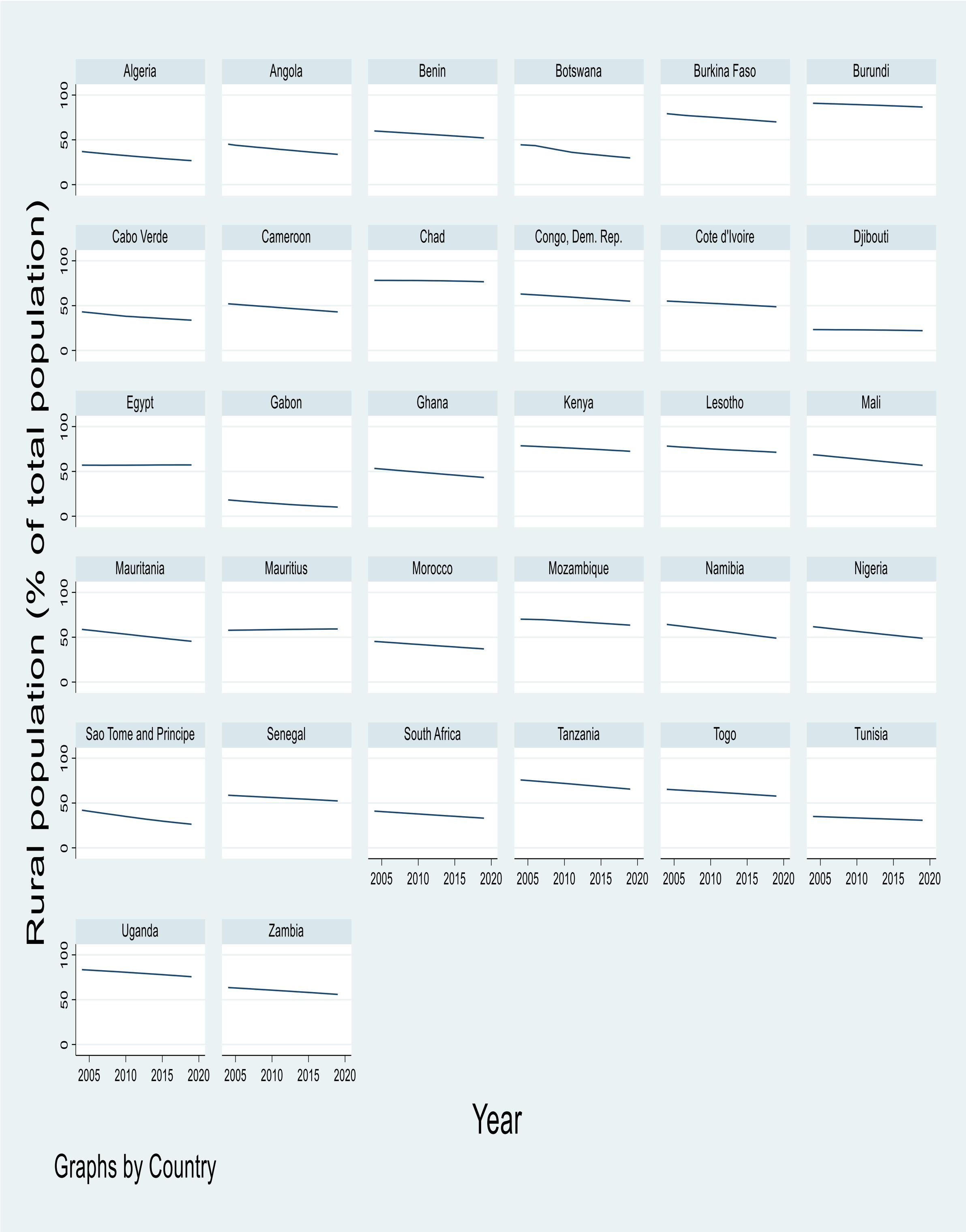

Figure 6. Trend of rural population across different African countries from 2004 to 2019.

Trend of net national income per capita across different African countries from 2004 to 2019 in Figure 7 shows that most of the countries studied exhibited increasing trend in per capita income. Similarly, the trend of domestic credit to the private sector by banks across different African countries from 2004 to 2019 shown in Figure 8 indicates that in many African countries, credit to the private sector is increasing.

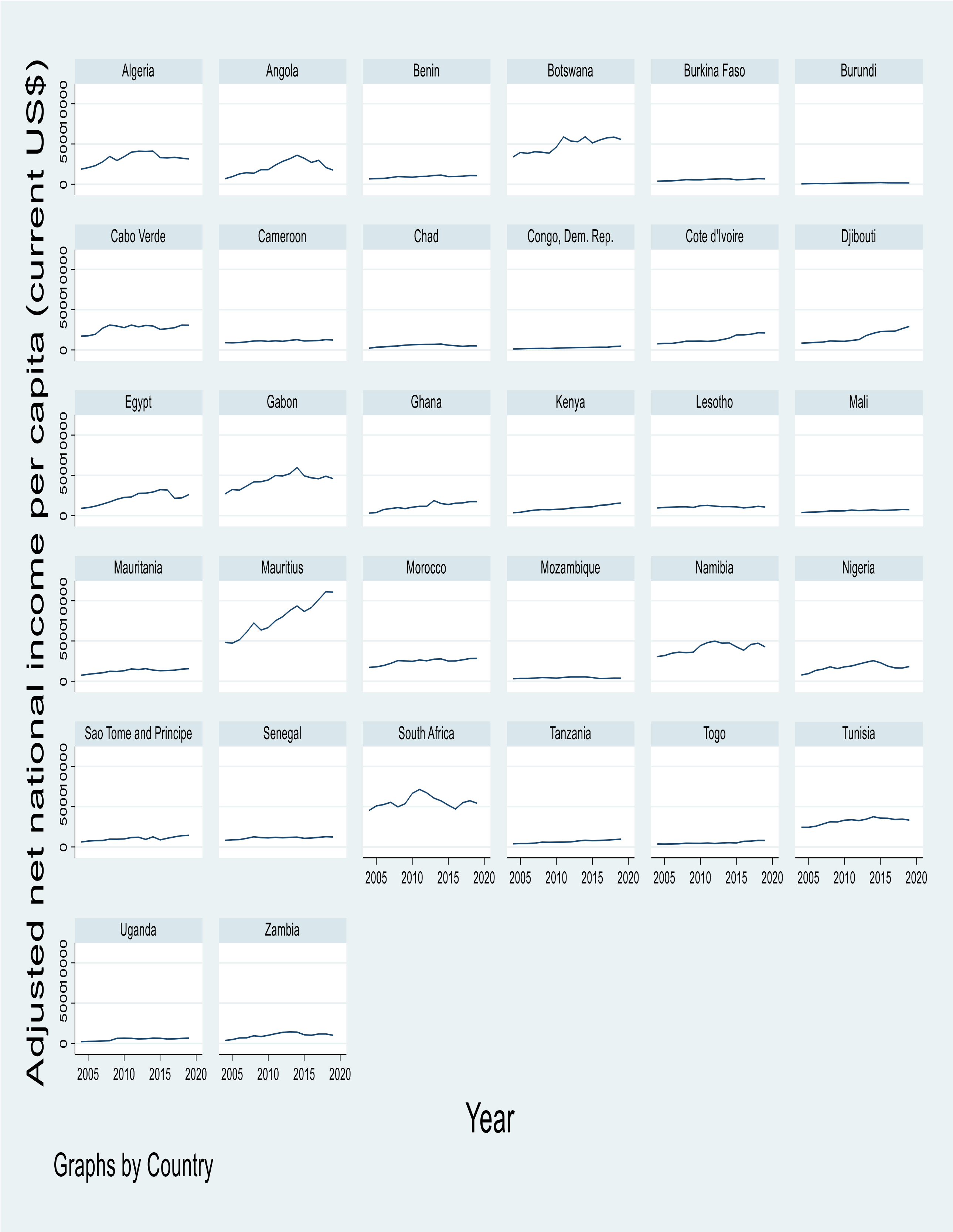

Figure 7. Trend of net national income per capita across different African countries from 2004 to 2019.

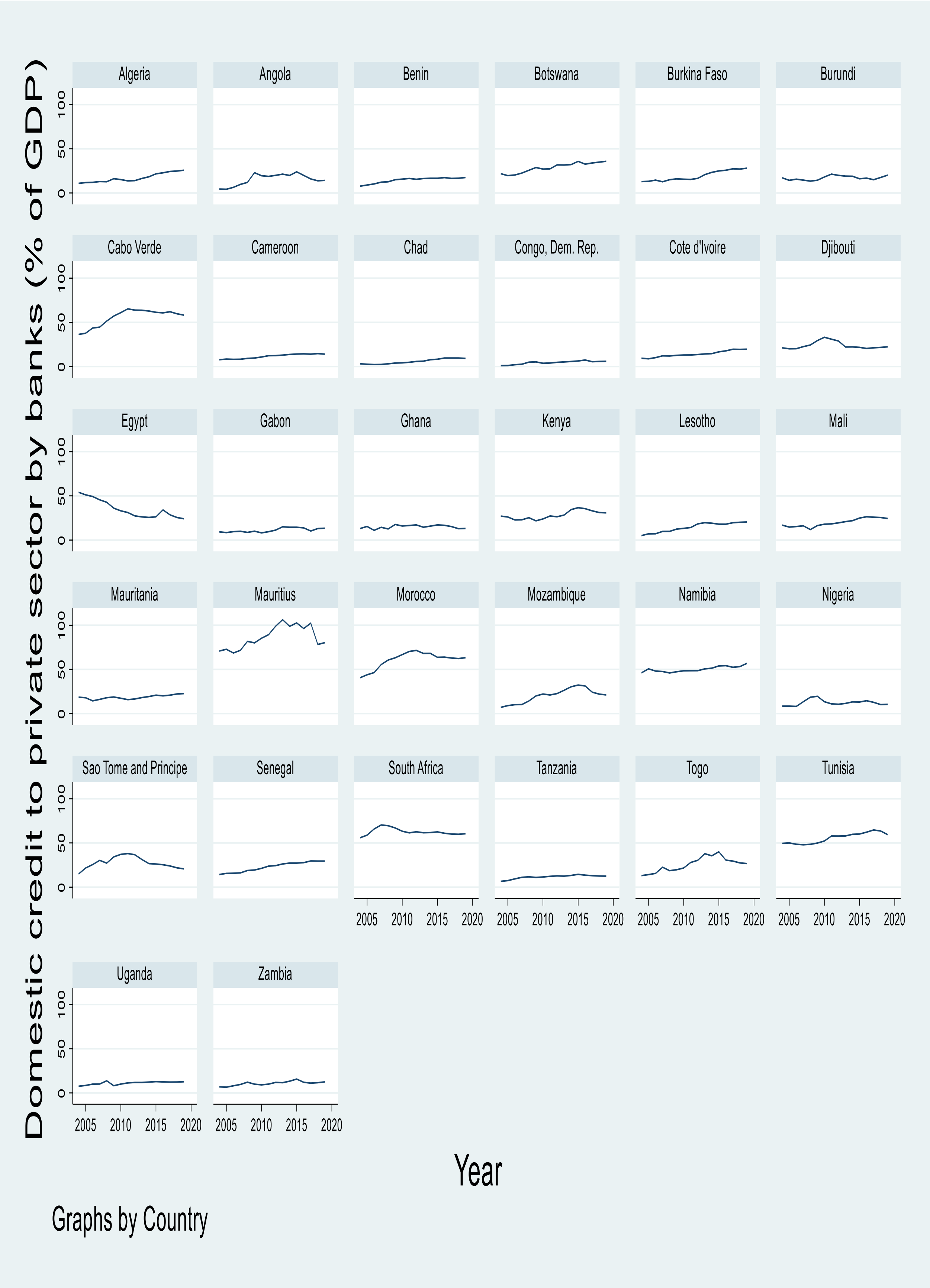

Figure 8. Trend of domestic credit to the private sector by banks across different African countries from 2004 to 2019.

4.3. Cross-Section Dependence Test

We rejected the null hypothesis of cross-section independence and infer the presence of cross-section dependence in our dataset, as shown by the *p*-values in Table 4.

Table 4. Cross-section dependence test.

Variable	CD-Test	*p*-Value
lnY1	44.00	0.000
lnY2	43.01	0.000
lnX1	85.04	0.000
lnX2	87.02	0.000
lnX3	7.99	0.000
lnX4	67.91	0.000
lnX5	42.08	0.000
lnX6	23.19	0.000

Variable list: Y1 = crop production index; Y2 = livestock production index; X1 = individuals using the internet (% of population); X2 = mobile cellular subscriptions (number of persons); X3 = fixed telephone subscriptions (number of persons); X4 = adjusted net national income per capita (current USD); X5 = domestic credit to private sector by banks (% of GDP); X6 = rural population (% of total population).

4.4. Multicollinearity Test for the Explanatory Variables

To determine whether the independent variables used in this paper are collinear, we subjected the explanatory variables to multicollinearity test using the variance inflation factor test. The result is presented in Table 5. The independent variables do not show the presence of multicollinearity, as none of the variance inflation factor values exceeded 5, which is a reasonable cut-off point for multicollinearity. Researchers have recommended variance inflation factors of less than 5 as an acceptable threshold for multicollinearity [74,75].

Table 5. Multicollinearity test using variance inflation factor (VIF).

Variable	Variance Inflation Factor (VIF)
lnX1	1.872
lnX2	3.467
lnX3	1.891
lnX4	3.452
lnX5	2.564
lnX6	2.090

Variable list: Y1 = crop production index; Y2 = livestock production index; X1 = individuals using the internet (% of population); X2 = mobile cellular subscriptions (number of persons); X3 = fixed telephone subscriptions (number of persons); X4 = adjusted net national income per capita (current USD); X5 = domestic credit to private sector by banks (% of GDP); X6 = rural population (% of total population).

4.5. Unit Roots Test of the Variables

It is customary to test the stationarity or otherwise before conducting an autoregressive distributed lag modeling [80–82]. This paper applied the Pesaran Cross-sectional Augmented Dickey–Fuller (CADF) and Im–Pesaran–Shin unit-root tests to determine stationarity of our dataset. The result of the unit-root test is presented in Table 6. The result shows that crop production index, livestock production index, mobile phone subscriptions, domestic credit provided to the private sector, and rural population were stationary at level under the Pesaran Cross-sectional Augmented Dickey–Fuller (CADF) test, while mobile phone subscriptions and rural population were stationary at level under the Im–Pesaran–Shin unit-root test. Individuals using internet, fixed telephone subscriptions, and net national income per capita have unit roots under the Pesaran Cross-sectional Augmented Dickey–Fuller (CADF) test, while crop production index, livestock production index, individuals using internet, fixed telephone subscriptions, net national income per capita, and domestic credit provided to the private sector have unit roots under the Im–Pesaran–Shin unit-root test. However, all the variables were stationary at the first difference under the Pesaran Cross-sectional Augmented Dickey–Fuller (CADF) and Im–Pesaran–Shin unit-root tests. This suggests that the panel ARDL model is appropriate in this case to model the impact of the independent variables on the dependent variable. Since all the variables were stable at first differencing, a further test to establish if there was a cointegration between the variables was conducted using the Pedroni test and Westerlund test.

Table 6. Unit root test.

H_0 = All Panels Contain Unit Roots H_0 = Series Have a Unit Roots				
Pesaran's CADF Test				
	At Level I(0)	**At First Difference I(1)**		
Variable	***t*-Statistic**	***t*-Statistic**	**Decision: H_0**	**Result**
lnY1	−2.255 ***	−3.021 ***	Reject	I(0) at 1%
lnY2	−2.035 **	−2.503 ***	Reject	I(0) at 5%
lnX1	−2.014	−2.102 **	Reject	I(1) at 5%
lnX2	−2.563 ***	−2.956 ***	Reject	I(0) at 1%
lnX3	−1.795	−2.333 ***	Reject	I(1) at 1%
lnX4	−1.668	−2.740 ***	Reject	I(1) at 1%
lnX5	−2.185 ***	−2.608 ***	Reject	I(0) at 1%
lnX6	−2.327 ***	−3.399 ***	Reject	I(0) at 1%
Im–Pesaran–Shin unit-root test				
	At Level I(0)	**At First Difference I(1)**		
Variable	***t*-Statistic**	***t*-Statistic**	**Decision: H_0**	**Result**
lnY1	−0.8175	−8.6710 ***	Reject	I(1) at 1%
lnY2	0.2771	−5.1729 ***	Reject	I(1) at 1%
lnX1	0.2727	−3.3191 ***	Reject	I(1) at 1%
lnX2	−2.3181 **	−3.5185 ***	Reject	I(0) at 5%
lnX3	2.0290	−3.9593 ***	Reject	I(1) at 1%
lnX4	−0.1403	−5.9441 ***	Reject	I(1) at 1%
lnX5	−0.2970	−3.9756 ***	Reject	I(1) at 1%
lnX6	1.000	−13.347 ***	Reject	I(1) at 1%

Note: ** and *** indicate significance at 5% and 1% levels, respectively. Variable list: Y1 = crop production index; Y2 = livestock production index; X1 = individuals using the internet (% of population); X2 = mobile cellular subscriptions (number of persons); X3 = fixed telephone subscriptions (number of persons); X4 = adjusted net national income per capita (current USD); X5 = domestic credit to private sector by banks (% of GDP); X6 = rural population (% of total population).

4.6. Cointegration Test

The cointegration test presented in Table 7 reveals a long-run relationship between the dependent variables (crop production and livestock production) and independent variables (internet usage, fixed telephone subscriptions, mobile cellular subscriptions, net national income, credit to the private sector, and rural population). The results of the cointegration test using the Pedroni test and Westerlund test in Table 7 were all statistically significant, confirming the existence of cointegration between the dependent variables (crop production and livestock production) and independent variables (internet usage, fixed telephone subscriptions, mobile cellular subscriptions, net national income, credit to the private sector, and rural population) in Africa between 2004 and 2019.

4.7. Panel ARDL Elasticities of Impacts of Digital Tools on Agricultural Production

The Hausman test, which is a test for model misspecification helps detect endogenous variables in a model. With regards to the panel ARDL estimations, the pooled mean group (PMG) and dynamic fixed effect (DFE) estimators were employed. Since the aforementioned estimators' function under different assumptions, it is prudent to employ the Hausman test to determine the most efficient estimator (i.e., among PMG and DFE) for the analysis. The results garnered after performing the Hausman test on the two estimators indicate that the PMG estimator is the preferred estimator between the two estimators (Table 8). Thus, the PMG estimator was preferred for both the crop production category and livestock category. Henceforth, the PMG estimator is the most efficient estimator for the analysis as compared to the DFE estimator.

Table 7. Cointegration test.

H0: No Cointegration Ha: All Panels Are Cointegrated				
Pedroni Test for Cointegration	**Crop Production Index**		**Livestock Production Index**	
Test	**Statistic**	***p*-Value**	**Statistic**	***p*-Value**
Modified Phillips–Perron t	7.6234	0.0000	8.6877	0.0000
Phillips–Perron t	−20.8984	0.0000	−9.3796	0.0000
Augmented Dickey–Fuller t	−13.8666	0.0000	−7.5080	0.0000
Westerlund Test for Cointegration	**Crop Production**		**Livestock Production**	
Test	**Statistic**	***p*-Value**	**Statistic**	***p*-Value**
Variance ratio	−1.9163	0.03	−1.5991	0.05

Since the PMG estimator was the most efficient estimator among the three estimators, the study reported the PMG results. The results of the panel ARDL (using the PMG estimation technique) on the relationship between digital technologies and agricultural production (proxied by crop production and livestock production) in Africa can also be found in Table 8. Considering the long-run relationship, the results indicate that internet usage is statistically significant at 1% for crop production. Notice that the coefficient for internet usage recorded under the crop production is positive (0.071). Thus, the usage of internet positively influences crop production in these African countries listed in Table 1. All other things being equal, a percentage increase in the patronage of internet in these 32 African countries will increase their crop production index by 0.071%. This can be related to a recent study by Ma et al. [83] (2022), where they explored the influence of internet patronage on farmers' organic fertilizer application behavior. They established that internet significantly influences organic fertilizer positively, hence influencing crop production positively. On the other hand, the coefficient recorded for internet usage under the livestock production category was positive (0.017) but statistically insignificant. As more individuals in these countries patronize internet, the production of livestock increases too. This result is in line with expectation. The literature records a positive relationship between internet usage and livestock production (see [84–86]).

The next independent variable under consideration (mobile cellular subscription) was also statistically significant. The finding shows that mobile cellular subscription was statistically significant at 5% and 1%, respectively, under crop production and livestock production categories. The estimate recorded under the crop production was negative (−0.022). All other things being equal, a percentage increase in the mobile cellular subscription in the 32 African countries will decrease their crop production by approximately 0.022%. Thus, as more of the populace subscribes to a public mobile telephone service that provides access to the PSTN using cellular technology, these countries are highly probable to suffer a decline in their crop production index. The coverage of mobile phone networks in Africa is low and largely in urban areas where crop production is rarely practiced. Even those in rural areas with mobile cellular subscriptions may not use their mobile phones for obtaining agricultural production information and rather use the phones simply to connect with family and friends [61,87,88]. Therefore, owning a phone does not guarantee that the owner uses it to gather crop production information [89]. Further research is needed to explore the actual use of mobile phones by crop farmers. However, the estimate recorded under the livestock was positive. Thus, as more of the populace subscribes to a public mobile telephone service that provides access to the PSTN using cellular technology, these countries will increase their livestock production. This result can be related to the study by Houghton [90], who investigated the relationship between mobile cellular and livestock and established a stronger influence of mobile phone ownership and livestock production. Likewise, Nedumaran et al. [91] also emphasized that there is an impact of mobile phone patronage on crop production. The literature [1,64], however, shows that the use of mobile money accounts has inured positively to farmers' advantage.

Table 8. Panel ARDL results from pooled mean group and dynamic fixed effect estimators.

Variables	Crop Production		Livestock Production	
	PMG	**DFE**	**PMG**	**DFE**
Panel A: Long-Run Estimates				
lnX1	0.071	0.148	0.017	0.039
	(10.72) ***	(5.56) ***	(0.97)	(0.91)
lnX2	−0.022	−0.017	0.077	0.106
	(−1.97) **	(−0.50)	(5.17) ***	(1.90) *
lnX3	−0.031	−0.015	−0.079	0.008
	(−3.87) ***	(−1.28)	(−6.17) ***	(0.41)
lnX4	0.079	0.001	0.106	0.018
	(4.46) ***	(0.01)	(2.42) **	(0.15)
lnX5	0.006	0.141	0.392	0.009
	(0.44)	(2.34) **	(6.72) ***	(0.09)
lnX6	−0.293	−0.183	1.507	0.022
	(−10.34) ***	(−0.72)	(5.99) ***	(0.05)
Panel B: Short-Run Estimates				
ECT	0.690	0.481	0.191	0.170
	(6.47) ***	(11.94) ***	(4.42) ***	(6.16) ***
ΔlnX1	−0.051	−0.043	−0.018	0.003
	(−1.14)	(−1.22)	(−0.38)	(0.14)
ΔlnX2	0.120	0.007	0.008	0.007
	(1.96) **	(0.17)	(0.27)	(0.27)
ΔlnX3	−0.089	−0.002	−0.014	0.0002
	(−1.77) *	(−0.19)	(−0.25)	(0.03)
ΔlnX4	0.102	0.091	−0.005	0.038
	(0.87)	(1.79)*	(−0.08)	(1.31)
ΔlnX5	0.022	−0.038	−0.003	−0.006
	(0.19)	(−0.88)	(−0.06)	(−0.23)
ΔlnX6	1.969	−0.247	0.656	−0.061
	(1.33)	(−0.22)	(0.78)	(−0.10)
Constant	−3.857	−2.335	0.754	−0.404
	(−6.27) ***	(−4.14) *	(4.87) ***	(−1.29)
Observations	512	512	512	512

Hausman test of poolability (*H_0*: difference in coefficients not systematic)

	Crop production	**Livestock production**
	PMG and DFE	PMG and DFE
$\chi^2(6)$	2.32	0.07
p-value	0.8885	1.000
Decision	The PMG is preferred over the DFE	The PMG is preferred over the DFE

Note: z-values are presented in parenthesis. *** denotes statistical significance at 1%, ** denotes statistical significance at 5%, and * denotes statistical significance at 10%. Variable list: Y1 = crop production index; Y2 = livestock production index; X1 = individuals using the Internet (% of population); X2 = mobile cellular subscriptions (number of persons); X3 = fixed telephone subscriptions (number of persons); X4 = adjusted net national income per capita (current USD); X5 = domestic credit to private sector by banks (% of GDP); X6 = rural population (% of total population).

The variable "fixed telephone subscription" recorded negative and statistically significant relationships with crop production and livestock production. It was statistically significant at 1% and recorded a negative estimate (−0.031). Ceteris paribus, a percentage increase in the subscription of the fixed telephones in these African countries would decrease their crop production index by approximately 0.03%. Thus, as more of the populace subscribes to fixed telephones in these countries, their crop production index is expected to decrease in the long run. On the other hand, the fixed telephone subscription was highly significant (statistically significant at 1%). It also recorded a coefficient of −0.079. Thus, holding all other variables constant, a percentage increase in the subscription of fixed telephones in these African countries will decrease their crop production by approximately 0.079%. This implies that, as more of the populace from the aforementioned countries subscribes to the fixed telephone, the livestock production in these countries is expected to decline in the long run. Oyelami et al. [56] in their research found a long-run relationship between fixed telephone subscriptions with both crop and livestock production. The probable reason for the negative relationship between fixed telephone use and crop and livestock production could be due to the fact that fixed telephone subscription is low in the continent and they are not usually subscribed by farmers.

We observed that the variable "adjusted net national income per capita" was statistically significant under both crop production and livestock production categories. This implies that adjusted net national income per capita has a long-run relationship with both crop production and livestock production. It also recorded a coefficient of 0.106 for livestock production and 0.079 for crop production. Thus, the adjusted net national income per capita has a positive influence on crop and livestock production in these African countries. Statistically, livestock production in these African countries is expected to increase by 0.106% when there is an increase in the adjusted net national income per capita of these countries by a unit. Moreover, crop production index in these African countries is expected to increase by 0.079% when there is an increase in the adjusted net national income per capita of these countries by a unit. In a nutshell, we expect both crop and livestock production in these countries to increase in these counties in the long run when their adjusted net national income per capita increases.

Ironically, the variable "domestic credit to the private sector by bank" was not statistically significant under crop production category. This implies that the variable "domestic credit to private sector by bank" does not have a long-run relationship with crop production in these African countries. However, domestic credit to the private sector statistically increased livestock production. A unit increase in domestic credit to the private sector by the bank would increase livestock production index by 0.392. Credit is important in agricultural production [82].

Rural population was statistically significant at 1% for both crop and the livestock production categories. Again, the estimates recorded for rural population under the crop production and livestock production categories were −0.293 and 1.507, respectively. Thus, rural population negatively affects crop production but positively affects livestock production in the aforementioned 32 African countries. All other things being equal, a unit increase in rural population will decrease crop production by approximately 0.293%. On the other hand, we expect livestock production to increase by approximately 1.507% when there is a unit increase in rural population. In brief, we expect crop production to decrease in the long run when the rural population increases. This may be connected to increasing youth migration out of the rural areas to urban areas, which leaves a burden on the agricultural workforce. Livestock production is expected to increase in the long run when the rural population increases. This result conforms to most of the related literature [92–94].

With regards to the short-run results, notice that two out of the six variables were statistically significant under the crop production category and none were statistically significant under the livestock production category.

The first variable to consider under the short relationship is the mobile cellular subscriptions. From Table 8, it can clearly be seen that the variable is statistically significant under crop production. This implies that mobile cellular subscriptions have a significant influence on crop production in the 32 African countries in the short run. Holding all other variables constant, a percentage increase in mobile cellular subscriptions increased crop production in the aforementioned 32 African countries by approximately 0.12% in the short run. Mobile cellular subscriptions are not statistically significant for livestock production. This indicates that the variable "mobile cellular subscription" has no influence on livestock production in the 32 African countries in the short run. Chavula [50] observed similar findings using 10-year panel data, where they indicated that mobile phones had an insignificant impact on production.

We note that the variable "fixed telephone subscriptions" was not statistically significant under the livestock production category. Thus, fixed telephone subscription has no effect on livestock production in the 32 African countries in the short run. On the other hand, the variable was statistically significant at 10%. It also recorded an estimate of -0.089. This indicates a negative relationship between fixed telephone subscriptions and crop production in these countries in the short run. All other things being equal, an increase in fixed telephone subscriptions will decrease crop production in these African countries by approximately 0.089%. Thus, we expect crop production in these African countries to decline in the short run when more individuals patronize the internet. This result contradicts Chavula [50], who observed that fixed telephone lines positively impacted crop production.

4.8. Granger Test for Panel Causality

After examining whether there is a long-run relationship among our variables, it is appropriate to examine potential causal relationships among these variables. In determining the causal relationships among these variables, we employed the Dumitrescu and Hurlin [77] Granger test. Since the panel ARDL results (Table 8) establish the existence of long-run relationships among the variables, we are certain that Granger causality exists in at least one direction for each two-variable combination. Notice that the lag error terms (ECT_{t-1}) for internet patronage, mobile cellular subscription, fixed telephone subscription, adjusted net national income per capita, domestic credit to private sector by bank, and rural population were significant at the 1% significance level. This confirms the existence of at least a bidirectional causal relationship among the covariates and the response variables.

From the Dumitrescu and Hurlin test (Table 9), it can be seen clearly that majority of the Granger–causality relationship type found among the variables is bidirectional. Notice that bidirectional causality is found between crop production and internet patronage by populace of the 32 aforementioned African countries. Thus, crop production Granger causes internet patronage and internet patronage; also, Granger causes crop production. It can also be seen that there exists a bidirectional causality between livestock production and individuals using internet. From this knowledge, it can be said that livestock production Granger causes internet patronage, whereas internet patronage Granger also causes livestock production. The evidence provided from the analysis is not alien to the recent literature on agriculture production. In recent times, the use of internet in households and workplaces has been on the rise. The internet has become an integral part of life; it is now an essential global communications technology for business that aids in optimum dissemination of information and reduces the cost associated with interactions [95]. The adoption of internet in the agricultural industry has improved the efficiency and effectiveness in the sector [96]. The use of internet in the agricultural sector has aided in the following: access to market prices and products' information, access to government and academic reports and research results, interaction with other farmers and agricultural specialists, purchase of inputs, sales of produce, communication with suppliers and buyers, and access to software applications [96–98].

Similar to the relationship found between crop production and internet patronage, the relationship between crop production and mobile cellular subscription is bidirectional. Thus, crop production Granger causes mobile cellular subscription and mobile cellular subscription Granger also causes crop production. With regards to the other livestock production, the relationship type found with mobile cellular subscription is unidirectional. Thus, livestock production Granger causes mobile phone subscriptions; however mobile phone subscriptions Granger does not cause livestock production. Higher livestock production may lead to higher incomes that allow more mobile subscriptions and, at the same time, if non-subscribers see that subscription owners have higher production efficiency, that may be a motivation for them to subscribe too.

Table 9. Dumitrescu and Hurlin (D-H) Granger non-causality test results.

Hypothesis	Z-Bar	Z-Bar Tilde	Conclusion
lnY1 → lnX1	4.5283 ***	14.1133 ***	Bidirectional causality identified between crop production and individuals using internet
lnX1 → lnY1	5.2503 ***	3.1627 ***	
lnY1 → lnX2	14.7412 ***	9.9076 ***	Bidirectional causality identified between crop production and mobile phone subscriptions
lnX2 → lnY1	3.3658 ***	1.8234 *	
lnY1 → lnX3	7.8396 ***	5.0028 ***	Bidirectional causality identified between crop production and fixed telephone subscriptions
lnX3 → lnY1	3.9543 ***	2.2417 **	
lnY1 → lnX4	5.4957 ***	3.3371 ***	Bidirectional causality identified between crop production and net national income
lnX4 → lnY1	3.4100 ***	1.8549 *	
lnY1 → lnX5	6.8778 ***	4.3193 ***	Bidirectional causality identified between crop production and domestic credit to the private sector
lnX5 → lnY1	2.9885 ***	1.5553	
lnY1 → lnX6	13.5463 ***	9.0584 ***	Unidirectional causality identified. Crop production index does Granger cause rural population while rural population does not Granger cause crop production index.
lnX6 → lnY1	−0.2653	−0.7570	
lnY2 → lnX1	4.5346 ***	2.6541 ***	Bidirectional causality identified between livestock production and individuals using internet
lnX1 → lnY2	4.4845 ***	2.6185 ***	
lnY2 → lnX2	5.4399 ***	3.2975 ***	Unidirectional causality identified. Livestock production Granger cause mobile phone subscriptions, however mobile phone subscriptions does not Granger cause livestock production
lnX2 → lnY2	1.0341	0.1664	
lnY2 → lnX3	1.6378	0.5954	Unidirectional causality identified. Livestock production does not Granger cause fixed telephone subscriptions, however fixed telephone subscriptions does Granger cause livestock production
lnX3 → lnY2	6.4053 ***	3.9835 ***	
lnY2 → lnX4	1.5409	0.5265	Unidirectional causality identified. Livestock production does not Granger cause net national income, however net national income does Granger cause livestock production
lnX4 → lnY2	2.1615 **	0.9676	
lnY2 → lnX5	1.3615	0.3991	Unidirectional causality identified. Livestock production does not Granger cause domestic credit to the private sector, however domestic credit to the private sector does Granger cause livestock production.
lnX5 → lnY2	3.4853 ***	1.9083 *	
lnY2 → lnX6	7.0168 ***	4.4181 ***	Unidirectional causality identified. Livestock production index does Granger cause rural population while rural population does not Granger cause livestock production index.
lnX6 → lnY2	1.0497	0.1775	
lnX1 → lnX2	7.0461 ***	4.4389 ***	Bidirectional causality identified between individuals using internet and mobile cellular phone subscriptions
lnX2 → lnX1	12.6614 ***	8.4295 ***	
lnX1 → lnX3	5.9593 ***	3.6666 ***	Bidirectional causality identified between individuals using the internet and fixed telephone subscriptions
lnX3 → lnX1	8.7208 ***	5.6291 ***	
lnX1 → lnX4	6.5856 ***	4.1116 ***	Bidirectional causality identified between individuals using the internet and net national income
lnX4 → lnX1	5.0373 ***	3.0113 ***	
lnX1 → lnX5	3.8857 ***	2.1929 **	Bidirectional causality identified between individuals using the internet and domestic credit to the private sector
lnX5 → lnX1	9.6742 ***	6.3066 ***	
lnX1 → lnX6	13.9557 ***	9.3493 ***	Bidirectional causality identified between individuals using the internet and rural population
lnX6 → lnX1	8.6073 ***	5.5484 ***	
lnX2 → lnX3	−0.2384	−0.7380	Unidirectional causality identified. Mobile cellular phone subscriptions does not Granger cause fixed telephone subscriptions, however fixed telephone subscriptions does Granger cause mobile cellular phone subscriptions
lnX3 → lnX2	5.5889 ***	3.4033 ***	
lnX2 → lnX4	1.1834	0.2725	Unidirectional causality identified. Mobile cellular phone subscriptions does not Granger cause net national income, however net national income does Granger cause mobile cellular phone subscriptions
lnX4 → lnX2	5.6951 ***	3.4788 ***	
lnX2 → lnX5	3.8833 ***	2.1912 **	Bidirectional causality identified between mobile cellular phone subscriptions and domestic credit provided to the private sector by banks
lnX5 → lnX2	13.7153 ***	9.1785 ***	
lnX2 → lnX6	2.9612 ***	1.5359	Bidirectional causality identified between mobile cellular phone subscriptions and rural population
lnX6 → lnX2	2.2326 **	1.0181	
lnX3 → lnX4	5.7472 ***	3.5158 ***	Bidirectional causality identified between fixed telephone subscriptions and net national income
lnX4 → lnX3	2.0032 **	0.8551	
lnX3 → lnX5	8.8024 ***	5.6871 ***	Bidirectional causality identified between fixed telephone subscriptions and domestic credit provided to the private sector by banks
lnX5 → lnX3	7.8753 ***	5.0282 ***	
lnX3 → lnX6	9.2821 ***	6.0279 ***	Unidirectional causality identified. Fixed telephone subscriptions does Granger cause rural population while rural population does not Granger cause fixed telephone subscriptions.
lnX6 → lnX3	−0.3902	−0.8459	
lnX4 → lnX5	2.1153 ***	0.9347	Bidirectional causality identified between net national income and domestic credit provided to the private sector by banks
lnX5 → lnX4	13.3666 ***	8.9307 ***	
lnX4 → lnX6	3.3663 ***	1.8238 *	Unidirectional causality identified. Net national income does Granger cause rural population while rural population does not Granger cause net national income.
lnX6 → lnX4	0.7951	−0.0034	
lnX5 → lnX6	7.5513 ***	4.7979 ***	Bidirectional causality identified between domestic credit provided to the private sector by banks and rural population
lnX6 → lnX5	1.8286 *	0.7310	

Note: H_0: one variable does not Granger cause the other variable for at least one panel variable. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels.

Like the internet, mobile phones also give greater access to information. It has become the fastest and easy way of conveying information. Many studies of agricultural production have established a relationship between mobile phone usage and agriculture [99–102]. Khan et al. [100] emphasized that the patronage of mobile phones has become the most effective communication tool that has brought changes not only to the agriculture sector, but to the other industries as well. This sector is one of the sectors that rely mostly on information to be abreast with current farm practices to enhance productivity. In view of this, mobile phones come handy in this sector; they enable farmers to disseminate information at all levels in knowledge exchange, agricultural trade, and agricultural products [100,102].

Per the data, it can be found that there existed a bidirectional causality between crop production and net national income, whereas the relationship type that was found between livestock production and net national income is unidirectional. Thus, livestock production does not Granger cause net national income, but net national income does Granger cause livestock production. Olanipekun et al. [103] studied the effect of agriculture on the environment, conditional upon the level of income in a panel of 11 Central and West African countries for the period 1996 to 2015, using Pooled Mean Group (PMG), Mean Group (MG), and Augmented Mean Group (AMG) techniques; the literature establishes a long-run relationship between net national income and agriculture production.

With regards to the rural population variable, the relationship type that was found with both crop and livestock production was unidirectional. Thus, crop production Granger causes rural population, while rural population does not. Moreover, livestock production Granger causes rural population, while rural population does not Granger cause livestock production. Muyanga and Jayne [94] studied the effect of the rising rural population density on smallholder agriculture in Kenya. The authors established that there was a relationship between agriculture production and rural population.

5. Conclusions, Policy Implications, and Recommendations

This article interrogates the impact of information and communication technologies on agricultural production proxied by crop and livestock indexes in 32 African countries. Our paper finds a positive impact between individuals using internet and their crop production in the long run and found no significant impact on livestock production index in the short and long run. This implies that using internet in the long run leads to increased crop production but with no impact for livestock production. Internet-based information tools could be developed for smallholder farmers whilst a conscious effort is made to improve access and connectivity in rural areas. Given the no returns on investment in the livestock sector, it may be important to invest more in internet access for livestock farmers.

Mobile cellular phone subscriptions significantly decreased crop production in the long run. However, mobile cellular phone subscriptions significantly increased livestock production in the long run. This means that information and communication technology-based interventions are usually not panaceas for agricultural development. Such interventions need to be embedded in the overall rural economic development framework, with investments in infrastructure that would direct the use of mobile phones to enhance crop production.

Fixed phone subscriptions significantly decreased crop production in the long run but significantly decreased livestock production index in the long run. This implies that, as more of the populace from the African countries subscribe to the fixed telephone, both livestock and crop production in these countries are expected to decline in the long run. We encourage African governments to invest more in mobile phones to replace the fixed phone lines, given that mobile phone penetration has increased substantially in the region and tends to serve multiple uses relative to the fixed phone subscriptions. Net national income per capita significantly increased crop production in the short run and significantly increased livestock production in the long run. We encourage more targeted economic activities to improve net national income per capita, particularly in the rural areas where there are limited economic activities, even though such spaces contribute immensely to the agricultural production of most countries in Africa. Rural population significantly decreased crop production in the long run. Rural population significantly increased livestock production only in the long run. In a nutshell, we expect livestock production to increase in the long run when the rural population increases. The rural space needs to be targeted to make it more attractive to retain individuals already in the space and also lure more individuals into the rural areas to help curb the typical rural–urban migration. An industrialization agenda can be pursued to encourage value addition to the raw materials produced in the rural geographies. By doing so, decent employment and economic opportunities will be created.

The paper found bidirectional causality between crop production and internet patronage, livestock production and individuals using internet, crop production and mobile cellular subscription, crop production and net national income, rural population, and both crop and livestock production. A unidirectional relationship was observed between livestock production and net national income. The direction (bidirectional or unidirectional) of the causality has implications for targeting by governments in Africa to promote crop and animal production by paying more attention to the direction of the causality.

We suggest that governments within Africa pay more attention to the direction of the causality existing between the covariates and the agricultural production. Specifically, dedicated attention should be paid to livestock production, which remains low in the region to enhance net national income. We recommend that governments in Africa focus and increase funding investment in ICTs to foster increased agricultural production while addressing structural challenges that can increase access to digital agricultural technologies. Agricultural extension and advisory services should harness the potential of digital technologies to bridge the deficit in the agricultural extension to farmer ratio. Additional efforts are required by extension agents to build the capacity of smallholder farmers in the rural spaces to be adept with information and communication technologies. It might be useful if governments in Africa incentivize the telecommunication companies that extend coverage to rural areas with tax rebates and holidays to encourage rural inclusion in the digital space to close the digital divide eventually.

6. Limitations and Future Research

Our paper has provided insights into the impact information and communication technologies on agricultural production; however, there are some limitations that should be mentioned and future studies should focus on such areas. As a result of data limitations, our study focused on information and communication technologies, such as fixed telephone subscriptions, mobile cellular subscription, and individuals using the internet; it is important to note that future studies should focus on other aspects of ICTs and digital technologies.

The findings of the study may not be generalizable to other regions outside of Africa or to other agricultural sectors that were not included in the study. Hence, there is need for future research to focus on other agricultural sectors and regions outside of Africa.

The study relies on panel data from 32 African countries. These countries were selected because of data availability over the period studied. Future studies may increase the scope (number of countries and period) to gain deeper and better insights on the topic.

While the study identifies bidirectional causality between various factors and agricultural production, it is important to note that the causality may not be straightforward or direct. There may be other factors that affect the relationship between ICTs and agricultural production. Future studies should investigate such factors.

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References

1. Kudama, G.; Dangia, M.; Wana, H.; Tadese, B. Will digital solution transform Sub-Sahara African agriculture? *Artif. Intell. Agric.* **2021**, *5*, 292–300. [CrossRef]
2. World Bank. Individuals Using the Internet (% of Population)—Sub-Saharan Africa. 2023. Available online: https://data.worldbank.org/indicator/IT.NET.USER.ZS?locations=ZG (accessed on 10 March 2023).
3. GSMA. The Mobile Economy Sub-Saharan Africa 2022. Available online: https://www.gsma.com/mobileeconomy/wp-content/uploads/2022/10/The-Mobile-Economy-Sub-Saharan-Africa-2022.pdf (accessed on 10 March 2023).
4. Gillwald, A.; Mothobi, O. After Access 2018: A Demand-Side View of Mobile Internet from 10 African Countries. 2019. Available online: https://researchictafrica.net/wp/wp-content/uploads/2019/05/2019_After-Access_Africa-Comparative-report.pdf (accessed on 3 March 2023).
5. LIRNEasia. Understanding Digital Access and Use in the Global South: Final Technical Report. 2019. Available online: https://idl-bnc-idrc.dspacedirect.org/bitstream/handle/10625/59183/IDL-59183.pdf?sequence=2&isAllowed=y (accessed on 3 March 2023).
6. Atta-Ankomah, R. Credit for households in Ghana: Has mobile money (momo) improved inclusive access? *Sci. Afr.* **2022**, *16*, e01230. [CrossRef]
7. Atta-Ankomah, R.; Okyere, C.Y. Welfare Effects of Financial Inclusion Services in Ghana: A Comparative Analysis of Mobile Money and Other Financial Services. *Glob. Soc. Welf.* **2023**, *10*, 83–92. [CrossRef]
8. CEMA. Digital Farming: What Does It Really Mean? 2017; p. 9. Available online: https://www.cema-agri.org/images/publications/position-papers/CEMA_Digital_Farming_-_Agriculture_4.0__13_02_2017_0.pdf (accessed on 10 March 2023).
9. Bronson, K. Smart farming: Including rights holders for responsible agricultural innovation. *Technol. Innov. Manag. Rev.* **2018**, *8*, 7–14. [CrossRef]
10. Wolfert, S.; Ge, L.; Verdouw, C.; Bogaardt, M.J. Big data in smart farming—A review. *Agric. Syst.* **2017**, *153*, 69–80. [CrossRef]
11. Rose, D.C.; Chilvers, J. Agriculture 4.0: Broadening responsible innovation in an era of smart farming. *Front. Sustain. Food Syst.* **2018**, *2*, 87. [CrossRef]
12. Baierle, I.C.; da Silva, F.T.; de Faria Correa, R.G.; Schaefer, J.L.; Da Costa, M.B.; Benitez, G.B.; Benitez Nara, E.O. Competitiveness of Food Industry in the Era of Digital Transformation towards Agriculture 4.0. *Sustainability* **2022**, *14*, 11779. [CrossRef]
13. Adam, U. 'Farming 4.0' at the Farm Gates. 2016. Available online: https://www.euractiv.com/section/agriculture-food/opinion/farming-4-0-digital-technology-at-the-farm-gates/ (accessed on 11 March 2019).
14. EurActiv. Farming 4.0: The Future of Agriculture? 2016. Available online: https://euractiv.eu/wp-content/uploads/sites/2/infographic/CEMA-18102016-EN-A4-V02-1.pdf (accessed on 10 March 2023).
15. Da Silveira, F.; Lermen, F.H.; Amaral, F.G. An overview of agriculture 4.0 development: Systematic review of descriptions, technologies, barriers, advantages, and disadvantages. *Comput. Electron. Agric.* **2021**, *189*, 106405. [CrossRef]
16. Schaefer, J.L.; Siluk, J.C.M.; de Carvalho, P.S. An MCDM-Based Approach to Evaluate the Performance Objectives for Strategic Management and Development of Energy Cloud. *J. Clean. Prod.* **2021**, *320*, 128853. [CrossRef]
17. Pivoto, D.; Barham, B.; Waquil, P.D.; Foguesatto, C.R.; Corte, V.F.D.; Zhang, D.; Talamini, E. Factors Influencing the Adoption of Smart Farming by Brazilian Grain Farmers. *Int. Food Agribus. Manag. Rev.* **2019**, *22*, 571–588. [CrossRef]
18. Fielke, S.; Taylor, B.; Jakku, E. Digitalisation of Agricultural Knowledge and Advice Networks: A State-of-the-Art Review. *Agric. Syst.* **2020**, *180*, 102763. [CrossRef]
19. Balducci, F.; Impedovo, D.; Pirlo, G. Machine Learning Applications on Agricultural Datasets for Smart Farm Enhancement. *Machines* **2018**, *6*, 38. [CrossRef]
20. Baierle, I.C.; Sellitto, M.A.; Frozza, R.; Schaefer, J.L.; Habekost, A.F. An Artificial Intelligence and Knowledge-Based System to Support the Decision-Making Process in Sales. *S. Afr. J. Ind. Eng.* **2019**, *30*, 17–25. [CrossRef]
21. Lioutas, E.D.; Charatsari, C.; La Rocca, G.; De Rosa, M. Key Questions on the Use of Big Data in Farming: An Activity Theory Approach. *NJAS—Wageningen J. Life Sci.* **2019**, *90–91*, 100297. [CrossRef]
22. Van der Burg, S.; Bogaardt, M.J.; Wolfert, S. Ethics of Smart Farming: Current Questions and Directions for Responsible Innovation towards the Future. *NJAS—Wageningen J. Life Sci.* **2019**, *90–91*, 100289. [CrossRef]
23. Lee, Y.Y.; Falahat, M.; Sia, B.K. Impact of Digitalization on the Speed of Internationalization. *Int. Bus. Res.* **2019**, *12*, 1–11. [CrossRef]
24. Nawandar, N.K.; Satpute, V.R. IoT Based Low Cost and Intelligent Module for Smart Irrigation System. *Comput. Electron. Agric.* **2019**, *162*, 979–990. [CrossRef]
25. Moon, A.; Kim, J.; Zhang, J.; Son, S.W. Evaluating Fidelity of Lossy Compression on Spatiotemporal Data from an IoT Enabled Smart Farm. *Comput. Electron. Agric.* **2018**, *154*, 304–313. [CrossRef]
26. Quiroz, I.A.; Alférez, G.H. Image Recognition of Legacy Blueberries in a Chilean Smart Farm through Deep Learning. *Comput. Electron. Agric.* **2020**, *168*, 105044. [CrossRef]
27. Gacar, A.; Aktas, H.; Ozdogan, B. Digital Agriculture Practices in the Context of Agriculture 4.0. *Pressacademia* **2017**, *4*, 184–191.
28. Janc, K.; Czapiewski, K.; Wójcik, M. In the Starting Blocks for Smart Agriculture: The Internet as a Source of Knowledge in Transitional Agriculture. *NJAS—Wageningen. J. Life Sci.* **2019**, *90–91*, 100309. [CrossRef]
29. Mistry, I.; Tanwar, S.; Tyagi, S.; Kumar, N. Blockchain for 5G-Enabled IoT for Industrial Automation: A Systematic Review, Solutions, and Challenges. *Mech. Syst. Signal Process* **2020**, *135*, 106382. [CrossRef]

30. Zambon, I.; Cecchini, M.; Egidi, G.; Saporito, M.G.; Colantoni, A. Revolution 4.0: Industry vs. Agriculture in a Future Development for SMEs. *Process* **2019**, *7*, 36. [CrossRef]
31. Tsan, M.; Totapally, S.; Hailu, M.; Addom, B. The Digitalisation of African Agriculture Report 2018–2019. CTA. 2019. Available online: https://www.cta.int/en/digitalisation-agriculture-africa (accessed on 6 October 2020).
32. Muyiramye, D.; Addom, B.K. COVID-19 and Agriculture in Africa: Implications for Digitalisation. 2020. Available online: http://res.cloudinary.com/cta/raw/upload/v1601629259/1601629258808-COVID-19-and-Agriculture-in-Africa-implications-for-Digitalisation.pdf (accessed on 10 March 2023).
33. Schroeder, K.; Lampietti, J.; Elabed, G. *What's Cooking: Digital Transformation of the Agrifood System*; Agriculture and Food Series; World Bank: Washington, DC, USA, 2021.
34. Trendov, N.M.; Varas, S.; Zeng, M. Digital Technologies in Agriculture and Rural Areas *Briefing Paper*; p. 26. Food and Agriculture Organization of the United Nations: Rome, Italy. 2019. Available online: http://www.fao.org/3/ca4887en/ca4887en.pdf (accessed on 10 March 2023).
35. Goedde, L.; McCullough, R.; Ooko-Ombaka, A.; Pais, G. *How Digital Tools Can Help Transform African Agri-Food Systems*; McKinsey & Company: Chicago, IL, USA, 2021; pp. 1–9.
36. Harkin, M. ICT Adoption as an Agricultural Information Dissemination Tool: A Historical Perspective. 2007. Available online: https://economics.agri.huji.ac.il/sites/default/files/agri_economics/files/gelb-harkin-3.pdf (accessed on 10 March 2023).
37. May, J.; Karugia, J.; Ndokweni, M. Information and Communication Technologies and Agricultural Development in Sub-Saharan Africa: Transformation and Employment Generation (Final Framework Paper Prepared for the African Economic Research Consortium, AERC). 2007. Available online: https://www.africaportal.org/publications/information-and-communication-technologies-and-agricultural-development-in-sub-saharan-africa-transformation-and-employment-generation/ (accessed on 10 March 2023).
38. Cariolle, J. International connectivity and the digital divide in Sub-Saharan Africa. *Inf. Econ. Policy* **2021**, *55*, 100901. [CrossRef]
39. Garba, A.M. Agri-tech opportunities at the bottom of the pyramid: How big is the opportunity and how little has been exploited? Some selected cases in Nigeria. In *Digital Entrepreneurship in Sub-Saharan Africa: Challenges, Opportunities and Prospects*; Taura, N.D., Bolat, E., Madichie, N.O., Eds.; Springer International Publishing: Berlin/Heidelberg, Germany, 2019; pp. 199–220. [CrossRef]
40. United Nations Department of Economic and Social Affairs. *United Nation e-Government Survey: Gearing e-Government to support Transformation towards Sustainable and Resilient Societies*; United Nations: Washington, DC, USA, 2018; Available online: https://publicadministration.un.org/egovkb/Portals/egovkb/Documents/un/2018-Survey/E-Government%20Survey%202018_FINAL%20for%20web.pdf (accessed on 10 March 2023).
41. Aker, J.C. Dial "A" for agriculture: A review of information and communication technologies for agricultural extension in developing countries. *Agric. Econ.* **2011**, *42*, 631–647. [CrossRef]
42. Jensen, R. The digital provide: Information (technology), market performance, and welfare in the South Indian Fisheries Sector. *Q. J. Econ.* **2007**, *122*, 879–924. [CrossRef]
43. Thompson, T.; Gyatso, T. Technology Adoption for Improving Agricultural Productivity in Sub-Saharan Africa. Global Agricultural Productivity Report. 2020. Available online: www.globalagriculturalproductivity.org (accessed on 10 March 2023).
44. Li, X.; Guo, H.; Jin, S.; Ma, W.; Zeng, Y. Do farmers gain internet dividends from ecommerce adoption? Evidence from China. *Food Policy* **2021**, *101*, 102024. [CrossRef]
45. Ma, W.; Nie, P.; Zhang, P.; Renwick, A. Impact of internet use on economic wellbeing of rural households: Evidence from China. *Rev. Dev. Econ.* **2020**, *24*, 503–523. [CrossRef]
46. Zheng, H.; Ma, W.; Wang, F.; Li, G. Does internet use improve technical efficiency of banana production in China? Evidence from a selectivity-corrected analysis. *Food Policy* **2021**, *102*, 102044. [CrossRef]
47. Zhu, L.; Li, F. Agricultural data sharing and sustainable development of ecosystem based on block Chain. *J. Clean. Prod.* **2021**, *315*, 127869. [CrossRef]
48. Halewood, N.J.; Surya, P. *Mobilizing the Agricultural Value Chain in Information and Communication for Development-Maximising Mobile*; World Bank: Washington, DC, USA, 2012.
49. Aker, J.C.; Mbiti, I.M. Mobile phones and economic development in Africa. *J. Econ. Perspect.* **2010**, *24*, 207–232. [CrossRef]
50. Chavula, H.K. The role of ICTs in agricultural production in Africa. *J. Dev. Agric. Econ.* **2014**, *6*, 279–289.
51. Ker, J.C.; Fafchamps, M. Mobile phone coverage and producer markets: Evidence from West Africa. *World Bank Econ. Rev.* **2015**, *29*, 262–292.
52. Mramba, N.; Rumanyika, J.; Apiola, M.; Suhonen, J. ICT for informal workers in sub-Saharan Africa: Systematic review and analysis. In Proceedings of the 2017 IEEE AFRICON, Cape Town, South Africa, 18–20 September 2017; pp. 486–491.
53. Oladele, O.I. Effect of information communication technology (ICT) on agricultural information access among extension officers in North West Province South Africa. *S. Afr. J. Agric. Ext.* **2015**, *43*, 30–41. [CrossRef]
54. Sen, S.; Choudhary, V. Module 10: ICT applications for smallholder inclusion in agribusiness supply chains. In *ICT in Agriculture: Connecting Smallholders to Knowledge, Networks and Institutions E-Source Book*; World Bank: Washington, DC, USA, 2011; Available online: https://cto.int/wp-content/themes/solid/_layout/dc/k-r/ICT_in_Ag_Sourcebook_web_light.pdf (accessed on 3 March 2023).
55. Nguimkeu, P.; Okou, C. Leveraging digital technologies to boost productivity in the informal sector in Sub-Saharan Africa. *Rev. Policy Res.* **2021**, *38*, 707–731. [CrossRef]

56. Oyelami, L.O.; Sofoluwe, N.A.; Ajeigbe, O.M. ICT and agricultural sector performance: Empirical evidence from sub-Saharan Africa. *Future Bus. J.* **2022**, *8*, 18. [CrossRef]
57. Klerkx, L.; Jakku, E.; Labarthe, P. A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda. *NJAS-Wagening. J. Life Sci.* **2019**, *90*, 100315. [CrossRef]
58. Barrett, H.; Rose, D.C. Perceptions of the fourth agricultural revolution: What's in, what's out, and what consequences are anticipated? *Sociol. Rural.* **2022**, *62*, 162–189. [CrossRef]
59. Evans, O. *Digital Agriculture: Mobile Phones, Internet & Agricultural Development in Africa*; MPRA Paper 90359; University Library of Munich: Munich, Germany, 2018.
60. Suroso, A.I.; Fahmi, I.; Tandra, H. The Role of Internet on Agricultural Sector Performance in Global World. *Sustainability* **2022**, *14*, 12266. [CrossRef]
61. Quandt, A.; Salerno, J.D.; Neff, J.C.; Baird, T.D.; Herrick, J.E.; McCabe, J.T.; Xu, E.; Hartter, J. Mobile phone use is associated with higher smallholder agricultural productivity in Tanzania, East Africa. *PLoS ONE* **2020**, *15*, e0237337. [CrossRef]
62. Sennuga, S.O.; Conway, J.S.; Sennuga, M.A. Impact of information and communication technologies (ICTS) on agricultural productivity among smallholder farmers: Evidence from Sub-Saharan African communities. *Int. J. Agric. Ext. Rural. Dev. Stud.* **2020**, *7*, 27–43.
63. Irungu, K.R.G.; Mbugua, D.; Muia, J. Information and Communication Technologies (ICTs) attract youth into profitable agriculture in Kenya. *East Afr. Agric. For. J.* **2015**, *81*, 24–33. [CrossRef]
64. Kabbiri, R.; Dora, M.; Kumar, V.; Elepu, G.; Gellynck, X. Mobile phone adoption in agri-food sector: Are farmers in Sub-Saharan Africa connected? *Technol. Forecast. Soc. Chang.* **2018**, *131*, 253–261. [CrossRef]
65. Ogbeide, O.A.; Ele, I. Smallholder farmers and mobile phone technology in Sub-Sahara Agriculture. *Mayfair J. Inf. Technol. Manag. Agric.* **2015**, *1*, 1–19.
66. Ali, S.; Jabeen, U.A.; Nikhitha, M. Impact of ICTs on Agricultural Productivity. *Eur. J. Bus. Econ. Account.* **2016**, *4*, 82–92.
67. Dagne, T.W.; Oguamanam, C. ICTs in Agricultural Production and Potential Deployment in Operationalising Geographical Indications in Uganda. Ottawa Faculty of Law Working Paper No. 2018-24. 2018. Available online: http://dx.doi.org/10.2139/ssrn.3241169 (accessed on 10 March 2023).
68. Lechman, E.; Popowska, M. Harnessing digital technologies for poverty reduction. Evidence for low-income and lower-middle income countries. *Telecommun. Policy* **2022**, *46*, 102313. [CrossRef]
69. Welde, A.A. Digital Divide in Sub-Saharan Africa: A Panel Analysis of Internet Diffusion. In *Proceedings of the Eighteenth International Conference on the Ethiopian Economy*; Ethiopian Economics Association (EEA): Addis Ababa, Ethiopia, 2022.
70. Masuka, B.; Matenda, T.; Chipomho, J.; Mapope, N.; Mupeti, S.; Tatsvarei, S.; Ngezimana, W. Mobile phone use by small-scale farmers: A potential to transform production and marketing in Zimbabwe. *S. Afr. J. Agric. Ext.* **2016**, *44*, 121–135. [CrossRef]
71. Khan, N.; Ray, R.L.; Zhang, S.; Osabuohien, E.; Ihtisham, M. Influence of mobile phone and internet technology on income of rural farmers: Evidence from Khyber Pakhtunkhwa Province, Pakistan. *Technol. Soc.* **2022**, *68*, 101866. [CrossRef]
72. Khan, N.; Ray, R.L.; Kassem, H.S.; Ihtisham, M.; Asongu, S.A.; Ansah, S.; Zhang, S. Toward cleaner production: Can mobile phone technology help reduce inorganic fertilizer application? Evidence using a national level dataset. *Land* **2021**, *10*, 1023. [CrossRef]
73. Kaila, H.; Tarp, F. Can the Internet improve agricultural production? Evidence from Viet Nam. *Agric. Econ.* **2019**, *50*, 675–691. [CrossRef]
74. Chidiebere-Mark, N.M.; Onyeneke, R.U.; Uhuegbulem, I.J.; Ankrah, D.A.; Onyeneke, L.U.; Anukam, B.N.; Chijioke-Okere, M.O. Agricultural production, renewable energy consumption, foreign direct investment, and carbon emissions: New evidence from Africa. *Atmosphere* **2022**, *13*, 1981. [CrossRef]
75. Emenekwe, C.C.; Onyeneke, R.U.; Nwajiuba, C.U. Financial development and carbon emissions in Sub-Saharan Africa. *Environ. Sci. Pollut. Res.* **2022**, *29*, 19624–19641. [CrossRef]
76. Kumar, P.; Sahu, C.N.; Kumar, S.; Ansari, M.A. Impact of climate change on cereal production: Evidence from lower-middle-income countries. *Environ. Sci. Pollut. Res.* **2021**, *28*, 51597–51611. [CrossRef] [PubMed]
77. Dumitrescu, E.-I.; Hurlin, C. Testing for Granger non-causality in heterogeneous panels. *Econ. Model.* **2012**, *29*, 1450–1460. [CrossRef]
78. Hamadeh, N.; Rompaey, C.V.; Metreau, E.; Eapen, S.G. New World Bank Country Classifications by Income Level: 2022–2023. 2022. Available online: https://blogs.worldbank.org/opendata/new-world-bank-country-classifications-income-level-2022-2023 (accessed on 11 March 2023).
79. Cain, T.N. The Role of the Private Sector in Promoting Economic Growth and Reducing Poverty in the Indo-Pacific Region. Lowy Institute for International Policy. 2014. Available online: https://think-asia.org/bitstream/handle/11540/6707/LOWY-private-sector-indo-pacific.pdf?sequence=1 (accessed on 11 March 2023).
80. Emenekwe, C.C.; Onyeneke, R.U.; Nwajiuba, C.U. Assessing the combined effects of temperature, precipitation, total ecological footprint, and carbon footprint on rice production in Nigeria: A dynamic ARDL simulations approach. *Environ. Sci. Pollut. Res.* **2022**, *29*, 85005–85025. [CrossRef] [PubMed]
81. Onyeneke, R.U.; Emenekwe, C.C.; Adeolu, A.I.; Ihebuzor, U.A. Climate change and cattle production in Nigeria: Any role for ecological and carbon footprints? *Int. J. Environ. Sci. Technol.* **2022**, 1–14. [CrossRef]
82. Onyeneke, R.U.; Ejike, R.D.; Osuji, E.E.; Chidiebere-Mark, N.M. Does climate change affect crops differently? New evidence from Nigeria. *Environ. Dev. Sustain.* **2022**, 1–27. [CrossRef]

83. Ma, Q.; Zheng, S.; Deng, P. Impact of Internet Use on Farmers' Organic Fertilizer Application Behavior under the Climate Change Context: The Role of Social Network. *Land* **2022**, *11*, 1601. [CrossRef]
84. Akhigbe, B.I.; Munir, K.; Akinade, O.; Akanbi, L.; Oyedele, L.O. IoT technologies for livestock management: A review of present status, opportunities, and future trends. *Big Data Cogn. Comput.* **2021**, *5*, 10. [CrossRef]
85. Neethirajan, S.; Kemp, B. Digital livestock farming. *Sens. Bio-Sens. Res.* **2021**, *32*, 100408. [CrossRef]
86. Tzounis, A.; Katsoulas, N.; Bartzanas, T.; Kittas, C. Internet of Things in agriculture, recent advances and future challenges. *Biosyst. Eng.* **2017**, *164*, 31–48. [CrossRef]
87. Baird, T.D.; Hartter, J. Livelihood diversification, mobile phones and information diversity in Northern Tanzania. *Land Use Policy* **2017**, *67*, 460–471. [CrossRef]
88. Summers, K.H.; Baird, T.D.; Woodhouse, E.; Christie, M.E.; McCabe, J.T.; Terta, F.; Peter, N. Mobile phones and women's empowerment in Maasai communities: How men shape women's social relations and access to phones. *J. Rural. Stud.* **2020**, *77*, 126–137. [CrossRef]
89. Adenubi, O.; Temoso, O.; Abdulaleem, I. Has mobile phone technology aided the growth of agricultural productivity in sub-Saharan Africa? *S. Afr. J. Econ. Manag. Sci.* **2021**, *24*, 9. [CrossRef]
90. Houghton, D. Cell Phones and Cattle: The Impact of Mobile Telephony on Agricultural Productivity in Developing Nations. 2009. Available online: https://dukespace.lib.duke.edu/dspace/bitstream/handle/10161/1388/Houghton,%20Daniel.pdf?sequence=1 (accessed on 10 March 2023).
91. Huang, Z.; Zhuang, J.; Xiao, S. Impact of Mobile Internet Application on Farmers' Adoption and Development of Green Technology. *Sustainability* **2022**, *14*, 16745. [CrossRef]
92. Komarek, A.M.; Msangi, S. Effect of changes in population density and crop productivity on farm households in Malawi. *Agric. Econ.* **2019**, *50*, 615–628. [CrossRef]
93. Linh, D.H.; Cuc, N.T.T.; Tiep, N.C.; Diep, N.X.; Diep, V.B.; Busung, K.; Hung, N.N. The impact of agricultural growth on the rural development in Vietnam. *AgBioForum* **2019**, *21*, 48–56.
94. Muyanga, M.; Jayne, T.S. Effects of rising rural population density on smallholder agriculture in Kenya. *Food Policy* **2014**, *48*, 98–113. [CrossRef]
95. Smith, A.; Goe, W.R.; Kenney, M.; Paul, C.J.M. Computer and internet use by great plains farmers. *J. Agric. Resour. Econ.* **2004**, *29*, 481–500. [CrossRef]
96. Sujatha, R.; Nithya, R.A. A Survey on Soil Quality Testing using Sensors in Smart Agriculture for Crop Production and Maintenance using Internet of Things (IOT). *Int. J. Eng. Trends Technol.* **2017**, *7*, 55–59.
97. Ferrer, S.R.; Schroeder, D.H.; Ortmann, G.F. Internet Use and Factors Affecting Adoption of Internet Applications by Sugarcane Farm Businesses in the Kwazulunatal Midlands. In Proceedings of the 41st Annual Conference of the Agricultural Economic Association of South Africa (AEASA), Pretoria, South Africa, 2–3 October 2003.
98. Mishra, A.K.; Williams, R.P.; Detre, J.D. Internet access and internet purchasing patterns of farm households. *Agric. Resour. Econ. Rev.* **2009**, *38*, 240–257. [CrossRef]
99. Issahaku, H.; Abu, B.M.; Nkegbe, P.K. Does the use of mobile phones by smallholder maize farmers affect productivity in Ghana? *J. Afr. Bus.* **2018**, *19*, 302–322. [CrossRef]
100. Khan, N.A.; Qijie, G.; Ali, S.; Shahbaz, B.; Shah, A.A. Farmers' use of mobile phone for accessing agricultural information in Pakistan. *Ciência Rural. St. Maria* **2019**, *49*, e20181016. [CrossRef]
101. Khan, N.; Siddiqui, B.N.; Khan, N.; Khan, F.; Ullah, N.; Ihtisham, M.; Ullah, R.; Ismail, S.; Muhammad, S. Analyzing mobile phone usage in agricultural modernization and rural development. *Int. J. Agric. Ext.* **2020**, *8*, 139–147. [CrossRef]
102. Ogutu, S.O.; Okello, J.J.; Otieno, D.J. Impact of information and communication technology-based market information services on smallholder farm input use and productivity: The case of Kenya. *World Dev.* **2014**, *64*, 311–321. [CrossRef]
103. Olanipekun, I.O.; Olasehinde-Williams, G.O.; Alao, R.O. Agriculture and environmental degradation in Africa: The role of income. *Sci. Total Environ.* **2019**, *692*, 60–67. [CrossRef]