agriculture

Article

ICT and Agricultural Development in South Africa: An Auto-Regressive Distributed Lag Approach

Simion Matsvai * and Yiseyon Sunday Hosu

Department of Business Management and Economics—Small-Scale Agribusiness and Rural Non-Farm Enterprise Research Niche, Faculty of Economic and Financial Sciences, Walter Sisulu University, Private Bag X1, Mthatha 5117, South Africa; yhosu@wsu.ac.za

* Correspondence: simmymatsvai@gmail.com or smatsvai@wsu.ac.za

Abstract: The use of Information Communication Technology (ICT) forms a significant component of the Fourth Industrial Revolution (4IR). This study examined the impact of ICT on agricultural development in South Africa utilizing time series data from 1995 to 2022. Agricultural development was measured through agricultural output and agriculture total factor productivity as dependent variables. Traditional factors of production (land, labor, and capital) together with ICT variables (mobile cellphone subscriptions, Internet usage, and fixed telephone subscriptions) were used. Additional variables such as inflation, human development, access to energy and climate change were used. Data analysis was performed using the ARDL approach. The findings revealed that mobile phone subscriptions and Internet usage positively affect agricultural output and ATFP in the short and long run despite having a negative effect through the second lag in the short run. Fixed telephone subscriptions negatively affect ATFP in the long run while affecting output negatively in the short run through the first lag. Land, human development index, access to energy, and capital generally exhibited an increasing effect on both agricultural output and ATFP both in the short and long run through the various models estimated. Climate change and inflation were generally found to affect both agricultural output and ATFP negatively in the short and long run. The study concluded that ICT plays a significant role in promoting agricultural output and total factor productivity growth. Recommendations included that the South African government should promote the digitalization of the agriculture sector through the provision of ICT infrastructure that can be utilized by both smallholder farmers and large-scale agricultural producers.

Keywords: ICT; agricultural development; ARDL

Citation: Matsvai, S.; Hosu, Y.S. ICT and Agricultural Development in South Africa: An Auto-Regressive Distributed Lag Approach. *Agriculture* **2024**, *14*, 1253. https://doi.org/10.3390/agriculture14081253

Academic Editors: Piotr Prus and Aksana Yarashynskaya

Received: 24 June 2024
Revised: 14 July 2024
Accepted: 16 July 2024
Published: 30 July 2024

1. Introduction

The use of Information Communication Technology (ICT) forms a significant component of the Fourth Industrial Revolution (4IR) in which tasks are performed digitally. However, climate change; drought; lack of relevant and user-friendly ICT and its enablers [1]; low investment in agriculture, including inadequately financed agricultural research and development; slow reform of agricultural policies; colonial and primitive agriculture education [2]; poor weather conditions; and migration urbanization and international migration (increased rural–urban and international migration) mainly of the economically active population [3,4] derails potential embedded ICT as both a necessary and sufficient condition for the 4IR to affect both agricultural sector development (agricultural output and total factor productivity growth) and economic development. The usage of ICTs globally through the consolidation of the global communication networks is rapidly growing [5,6]. The Fourth Industrial Revolution (4IR) has taken the development policies of many global economies, including the South African economy, by storm. The South African economy is significantly influenced by the agriculture sector mainly through ensuring economic growth, social development, food security, and sustainable natural resource management [7,8]. However, for the agriculture sector to flourish, ICTs play a fundamental role in the stimulation and dissemination of agricultural information [9].

Many countries, both developed and developing, have notably appreciated ICTs as a fundamental aspect of agricultural and economic digitalization and development [10]. In the global telecommunications market, Africa has been ranked as the fastest growing continent over the past two decades [11]. ICTs play a very significant role in the national development discourses of both developed and developing economies [5,12]. Agriculture still contributes a significant proportion of gross domestic product to the South African economy, hence the strategic promotion of ICTs to the agricultural sector provides significant opportunities for the agricultural sector's development (agricultural output and total factor productivity growth), translating to economic growth, food security, export growth, import substitution, employment creation, and poverty alleviation.

As indicated in FAO [13], for developing countries, ICTs may result in profound impacts on efficiency, resilience, and inclusion, while for developed nations, innovations such as the Internet of Things, big data and cloud computing are critical aspects of agricultural sector revolutionization. ICTs in this case encompass hardware, software, networks, and the tools for collecting, storing, processing, transmitting, and presenting information [11]. ICTs primarily include radio, television, telephones (fixed and mobile (basic cell phones and smartphones)), computers, Internet technologies (fixed and mobile broadband), and databases that disseminate information. For many Sub-Saharan African economies, one of the key economic sectors is the agriculture sector. For the South African economy, appreciating the fundamental role of ICTs in economic growth [10,12,14–16] will therefore call for the application of such technologies in primary sectors including the agriculture sector. Various studies have investigated the impact of ICTs on agriculture and found varying impacts and relationships depending on the proxies used to measure ICT (mobile phone subscriptions, fixed telephone subscriptions, Internet subscriptions, mobile penetration rate, and Internet penetration rate). This is because the agriculture sector contributes significantly to economic growth, employment creation, food security, poverty alleviation, and livelihoods within the South African economy [7]. As that, this study is focused on an empirical investigation of the relationship between ICTs (fixed telephone subscriptions, mobile phone subscriptions and Internet usage) and agriculture total factor productivity and development. The study is also narrower than other studies that have examined the relationship between the two variables within a longitudinal framework, like [17–21]; meanwhile, others, like [1,9], were carried out within cross-sectional and micro-econometric frameworks.

ICTs such as mobile phone technology and the Internet are already revolutionizing the agricultural sector in many developing countries [22]. ICT applications can be used by farmers (for timely analysis and advice) to achieve better yields through the optimization of their crop and livestock management, together with resource reallocation [23]. The recent significant increase in the adoption of ICT technologies, mainly via telecommunications (that is, mobile and fixed phone technology), provides great opportunities for speeding up development in the agriculture sector through reductions in information and coordination costs, thereby helping farmers to gain access to critical forms of input such as seeds, fertilizers, and credit [13]. All these benefits will therefore help to fight poverty and improve food security. However, given the current and potential impact of ICTs in promoting agricultural development and economic growth, very few have been studied in the South African economy in relation to time series analysis, and in studies carried out in other countries, there is very little empirical evidence in relation to the impact of ICTs on agricultural development. Such studies include [19,24]. Thus, the purpose of this study is to provide empirical evidence on whether the recent increase in the uptake of mobile phone technology, Internet usage and the resurgence of the fixed telephones has had any relationship with agricultural sector development in terms of output and agricultural total factor productivity growth.

The potential impact of ICTs on the livelihoods and incomes of rural people can be assessed via agricultural production and productivity growth. The agriculture sector is the primary source of income in many developing economies, both rural and urban [13,25]. ICTS such as mobile phones have been identified as a key driver of the achievement of the SDGs [11,26,27]. With the growing population and the cumulative effects of climate change and the COVID-19 pandemic, the importance of food and nutrition cannot be overemphasized, as reflected in the United Nations' 2030 Agenda for Sustainable Development (SDG) through its 17 Sustainable Development Goals (SDGs). ICTs' application to the agriculture sector increases the chances of countries like South Africa making significant strides towards directly attaining the SDGs [28], such as SDGs 1, 2, and 13 (no poverty, zero hunger (through ending hunger and achieving food security, nutrition, and sustainable agriculture) and climate action), while the attainment of the rest of the SDGs can be enhanced indirectly. Food and nutritional security can be promoted through sustainable agriculture.

Agriculture for many agro-based economies has a significant role to play in ensuring economic growth, social development, food security, and sustainable natural resource management [7,8]. Sub-Saharan Africa (SSA) continues to be heavily dependent on the agriculture sector, contributing, on average, about 15% of the total gross domestic product. It employs over 50% of the rural populace [29], contributing on average about 15% of the total gross domestic product and 10% of exports [30]. However, despite the significant contributions of the agriculture sector to many African economies, compared to other countries and regions, there are still food insecurity and food crises due to low agricultural productivity caused by slow adjustment to digitalization. With access to Information and Communication Technology (ICT), agricultural activities can be promoted and made easier [2]. By increasing agricultural production, most of the SDGs will be met, whether directly or indirectly [8,28].

ICTs does not only promote the utilization of modern production techniques for productivity growth, but it also increases access to the markets and bridges the information gap between farmers and the market (reduces information asymmetry) and thereby increasing profitability and reduction in post-harvest losses. ICTs improved market access [31,32]. Apart from better production and profitability of agriculture, ICTs also help in the mitigation of climatic disaster losses and reducing air pollution [21]. Therefore, ICTs since it results in the reduction of carbon emissions, it results in reduction in climate change and its impact on agriculture [21]. ICTs, to the agriculture sector result in better agricultural production approaches, methods, tools, productivity, and market access [32].

In recent years, empirical evidence of the impact of (ICT) on agricultural development, has been growing [13] but much centered on the impact of ICTs to either agricultural output (agriculture value added) [19,22,33], or economic growth [16,34,35]. Little attention has been given to the relationship between ICT and agricultural development in the context of production and productivity growth. Agriculture is fast becoming knowledge-intensive and the knowledge in modern day economies is acquired through ICTs. Given that, information is currently one of the most valuable resources especially agricultural information if the agriculture sector is to be developed (both partial and total factor productivity from micro to macro lenses).

Through ICTs in agriculture, precision agriculture [(Remote sensing, Global Positioning System (GPS), Geographic Information System (GIS), IoT Internet of Things (IoT) and Machine learning algorithms (MLA)] will be possible. Through precision agriculture, farmers will be able to engage in yield monitoring, soil mapping, crop health monitoring, automated irrigation and crop planning and management [13]. As a result of ICTs enabled precision agriculture, productivity, cost saving, resource efficiency (optimal input vector/combinations), environmental sustainability, quality agricultural decisions (data-driven insights), climate change adaptation, targeted interventions, and efficiency (technical, scale, X and profit efficiency) will ultimately increase through ICTs. ICTs enables Artificial Intelligence (AI) to be incorporated into agricultural production and productivity because it can be used to analyze data to help farmers optimize the efficiency and sustainability of their farming practices. Information services are one of the most common ICT-related categories for inclusive agricultural value chains [36,37]. The sub-categories of information services involve short and long-term productivity enhancements (those that minimize the negative effects of crisis events, and those that improve field- based risk management), [13]. Given the vulnerability of the agriculture sector to several shocks like climate change, drought, and pandemics, without ICT, the sector will be characterized by under-productivity. In remoter areas of South Africa, farmers often lack access to finance, property rights (land tenure systems) and market access.

The study seeks to examine both the short run and long run relationships between ICT and agricultural development in South Africa and the relationship between agricultural development and other variables (traditional factors of production such as land, labor, and capital, together with other determinants of agricultural production and productivity such as climate change, access to energy, general price level and human development index). For the sake of this study, mobile cellphone subscriptions, Internet usage and fixed telephone subscriptions were used as proxies for ICTs as the study seeks to investigate the nexus between ICTs (mobile cellphone subscriptions, Internet usage and fixed telephone subscriptions) and agricultural development (output and total factor productivity) in South Africa. The following sections entail a problem statement, the significance of this research, a literature review, the research methodology, presentation and discussion of results and the conclusions, policy proposals, and further study recommendations.

1.1. Problem Statement

Despite the rapid growth in mobile and fixed phone subscriptions together with Internet penetration and usage rates, South Africa is fast becoming food-insecure and nutritionally insecure. Poverty and malnutrition rates are growing cumulatively. With increasing rates of rural to urban migration, in the face of more than 80% of the South African population not being directly involved in agriculture (according to [38]), the traditional challenges of food inaccessibility and utilization are worsening with the new developing challenges of food insufficiency and unavailability. Simply put, despite the steady (i.e., increasing at a decreasing rate) growth in food (agriculture) production in South Africa, the population is growing (i.e., increasing at an increasing rate). Therefore, demand for food is rising faster than supply (causing excess demand for food). Rapid growth in the adoption and usage of ICTs is yet to bring significant returns to the South African agriculture sector. The traditional factors of production (land, labor, capital) are becoming more and more scarce, and land is in elastic in the face of land use change. In matching population growth with food production, despite inelastic factors of production (e.g., traditionally increasing the land involved in agricultural production in order to meet excess demand for food), ICTs may have a significant role to play. With the current competing uses of land, food production (which is growing arithmetically) is now lagging behind population growth (which is growing geometrically), as articulated in the Malthusian [39] growth model. Agricultural land is being lost to spreading urban and industrial areas, thereby worsening food insecurity and increasing vulnerability to shocks and climate change on the part of the South African economy. The prevalence of moderate to severe food insecurity is constantly rising in South Africa [13] despite growth in the adoption of ICTs (mobile cellphone subscriptions, fixed telephone subscriptions and the Internet). Migration in the South African context (which, for the economically active population, skews towards rural to urban migration) is leaving economically inactive and less active people on farms, and hence food and nutritional insecurity are rising together with ICT adoption, despite the steady increase in agricultural production. The South African economy is among the biggest in Africa and a net supplier (exporter) of food at the national level, but it is characterized by food and nutritional insecurity at the household level due to more than 80 percent of households not being involved in agriculture [30].

1.2. Significance of This Study

The empirical literature on the impact of ICTs on the agriculture sector is biased towards longitudinal data-based studies [12,17,40–43] and even more skewed towards cross-sectional data; of these studies, the majority are further inclined to the adoption and usage of ICTs within micro-econometric frameworks [1,18,20,24,33,44–49]. For the few based on macroeconomic data, there is strong bias towards the impact of ICTs on agricultural output and value-added agriculture [19,22,33,50] and economic growth [16,34,35,51]; hence, this study seeks to fill this gap by extending the analysis to the impact of ICTs on agricultural development (agricultural output and ATFP). This is mainly because production is not precisely productivity, and determinants of production may not be determinants of productivity. Many studies that have tried to measure ICTs' impact on productivity have used agricultural output, which is not the precise measure of productivity; hence, this study captured agricultural development though production and productivity growth by utilizing data from the USAID [52]. From previous studies, the findings were varied (inconclusive and inconsistent), and the findings were also dependent upon the proxies used to capture ICT variables. ICTs have a significant positive impact on agricultural output, and this was significantly more pronounced in higher-income than in lower-income countries [42]; Suroso [43] found that ICTs have a significant global effect on agricultural value addition. On the contrary, Suroso [43] also found that the role of the Internet in agricultural development is relatively greater in developing countries, while Chavula [17] found a positive association between the spread of ICT and agricultural productivity in Africa. On the other hand, Oyelami [12] found only positive long-term effects of ICT on agricultural sector performance. Meanwhile, on the causal relationship, Olaniyi [24] found bidirectional causality between ICTs and agricultural development. Additionally, Chandio [40] found that mobile phone subscriptions are positively related to cereal production from a panel dataset concerning seven Asian countries. Despite the inconclusiveness of the findings from various studies, the results speak less to country-specific outcomes; therefore, this study focuses on South Africa in order to produce country-specific evidence on the relationship between ICTs and agricultural development (production and agriculture total factor productivity (ATFP)).

2. Literature Review

Rajkhowa and Baumüller [53] examined the impact of ICT on partial productivity (land and labor productivity) using data from 86 countries from 2000 to 2019, utilizing fixed-effects panel regression in a feasible generalized least squares approach. Their results revealed a positive and statistically significant association between ICT and both land and labor productivity in agriculture on a global scale. However, the magnitude of the effect was found to be much smaller than that for human capital, access to input, or environmental variables. Regionally, ICT uptake and land productivity were found to be insignificant in Africa and Asia, while labor productivity was found to be significant. Akinlo & Dada [54], using panel data for 26 Sub-Saharan African economies (2000 to 2019), examined the moderating role of real sector output in the ICT–economic growth nexus. Real sector output was proxied to three variables (industrial added value, agricultural added value, and total factor productivity) and ICT (proxied to mobile phones, fixed telephones, and Internet penetration). The pooled ordinary least squares (POLS), fixed-effects (within), and generalized least squares (Driscoll–Kraay standard error) were used to account for cross-sectional dependence. ICT was found to have mixed effects on economic growth. Resulting implications included that for countries to benefit from the potential of ICT growth, the real sector's absorptive capacity should be strengthened.

Oyelami [12] examined the effect of ICT infrastructure on the agricultural sector's performance in 39 Sub-Saharan African economies using a panel auto-regressive distributed lag (ARDL) approach for the period 1995–2017. Mobile phone subscriptions and Internet usage were the critical independent variables of ICT, and the livestock production index and crop production index were introduced as control variables. The results revealed substantial evidence that ICT infrastructure has long-term positive effects on agricultural sector performance, whilst in the short term, no evidence was found. Chavula [17] assessed the impact of ICT on agricultural production using 2000–2011 panel data for 34 African countries. The study concluded that ICT (fixed telephone lines) enhanced agricultural production, while mobile phones were found to have an insignificant impact on agricultural production despite the wide proliferation of mobile technologies and accelerated rate of mobile subscriptions. Chandio [40] examined the impact of ICT and technological development (i.e., fertilizer and pesticide usage) on cereal production in seven selected Asian economies using 2000 to 2018 data. CIPS, CADF, Westerlund bootstrap panel co-integration, Driscoll and Kraay (D–K), feasible generalized least square (FGLS), and Dumitrescu and Hurlin (D–H) causality methods were used for estimation. ICT was found to have a statistically significant and positive impact on cereal production in the long run, and a statistically significant two-way causal relationship running from selected co-integrated variables (i.e., ICT, fertilizers, pesticides, and land size) to cereal production was observed.

Olaniyi [19] examined the relationship between mobile phones, Internet, and agricultural development in Africa for the period 2001–2015 using a systemic generalized method of moments (GMM). The empirical results exhibited a non-linear positive relationship between mobile phones and agricultural development and a non-linear negative relationship between Internet use and agricultural development. Therefore, mobile penetration has an increasing effect on agricultural output, while Internet usage has a decreasing effect on agricultural output; overall Internet usage has significant positive effects. The study also found that mobile phones and Internet usage significantly affect agricultural development, and agricultural development significantly affects mobile phones and Internet usage (bidirectional causation). Ejemeyovwi and Osabuohien [50] empirically examined the role of ICT on agriculture. They used the crop production subsector from 1985–2014. Data were analyzed using ordinary least squares regression, and the results exhibited the positive impact of Internet utilization on crop production, while mobile cell phone subscriptions had a short-term negative impact. From the correlation results, ICT adoption and crop production proved to be strongly and positively associated.

Quandt [20] examined the impact of mobile phones on agricultural productivity and the relationships between mobile phone use and agricultural yield by fitting multilevel statistical models to data from phone-owning farmers in four rural communities in Tanzania. The results showed a positive association between mobile phone use for agricultural activities and maize yields (mobile phone use increased agricultural profits by 67% and decreased costs by 50% and time investments by 47%). Aminou [44] examined the effect of mobile phone ownership on agricultural productivity in Benin using the case of maize farmers. Micro-data were used, and a two-stage regression approach was employed. The results showed a significant positive relationship between mobile phone ownership and maize farmers' productivity (mobile phone ownership was specifically found to enhance maize production by 0.21 and 0.04 using the two estimated models). Mdoda [1] analyzed the factors influencing the use of information systems for enhancing smallholder production in the Eastern Cape Province of South Africa. The study applied a descriptive survey research design. A multi-stage random sampling technique was used on 220 emerging growers through a semi-structured survey questionnaire. Data analyses were performed using descriptive statistics and a logistic regression model. The findings indicated that agricultural productivity has been enhanced and food security status among rural households has been improved through the use of information systems. Recommendations were that the government need to embark on awareness and training campaigns for farmers to take advantage of information systems so that their productivity can be enhanced.

Mwalupaso [48] investigated the association between mobile phone adoption and farmers' technical efficiency (TE) in Zambia. A two-stage sampling procedure was used to select farmers, and a Cobb–Douglas (CD) production function was used in the conventional stochastic production frontier (SPF) and propensity score-matching–stochastic production frontier (PSM-SPF) model. The findings revealed that the use of mobile phones was significantly and positively associated with farmers' TE. Increasing mobile phone usage could be used to close the TE gap between farmers, meaning a general reduction in severe and extreme poverty. Recommendations include the promotion of mobile phone use in agricultural production. Olaniyi and Ismaila [24] assessed ICT usage and the household food security status of maize crop farmers in Ondo State, Nigeria. A multi-stage sampling technique was employed in selecting 212 maize farmers using structured interviews. Inferential statistics were used for data analysis. The findings revealed that cell phone (92.5%), radio (86.3%), and television (67.9%) were the most available ICT tools. Estimates of binary logit regression analysis showed that household size, membership of social organization, farm size, cell phone usage, and perception of the contribution of ICT usage were found to have significant effect on household food security status. The resulting recommendations were that institutions should concentrate on tools such as cell phones in disseminating relevant and timely information to farming households for sustainable food security.

3. Research Methodology

3.1. Conceptual Framework and Model Specification

The theoretical model is derived from the models of exogenous growth [55,56] and endogenous growth models. The exogenous growth models were captured by considering the conventional factors of production, and the endogenous growth models were captured by the inclusion of variables like the human development index and the disaggregated ICT variables (mobile cellphone subscriptions, Internet usage, and fixed telephone subscriptions). The baseline model was therefore based on works from previous studies [12,17,19], which adopted multivariate model specifications that include several choice and environmental variables perceived to affect domestic agricultural production.

$$Y_t = \varphi + \gamma ICT_t + \delta X_t + \varepsilon_t \quad (1)$$

where Y is output; ICT is either mobile cellphone subscriptions, Internet usage, or fixed telephone subscriptions; and X is a vector of other variables affecting output. ε is the error term (that captures the effect of other variables such as government expenditure on agriculture, agriculture subsidies, exchange rates, agriculture trade (exports and imports), natural disasters, agriculture credit and many others that have been excluded in the current study due to data availability and gaps), and t is the time (year). To compare the impact of various ICT components on agricultural development (production and ATFP), the researchers disaggregated ICT into mobile cellphone subscriptions (MOBS), fixed telephone subscriptions (FTS) and Internet subscriptions (INU), which were all incorporated with other variables. The study proxied the ICT variables as indicated above, following the works of [12] and also because when working with penetration rates like in [10], the researchers were worried about problems of multicollinearity. This is because all will be converted as a percentage of the total population (or per 100 people where the total population component exists). On the ICT variables, other researchers like [17] proxied education as an additional ICT variable, but in this study, for the same reasons of multicollinearity, we used the human development index (HDI) as one of the control variables because it captures education, health, and income components, thus providing an additional critical independent variable in the models that is estimated directly and related to the effective adoption and use of ICT. Like [19,24], who used primary education as a critical control variable (arguing that basic primary education enables individuals to be able to operate ICT gadgets), this study furthered that argument by arguing that not only basic education matters, but that health and income should also be incorporated, and we finally settled for the HDI. The resultant estimated models took the following forms, as presented below.

$$Y_t = \varphi + \gamma_1 MCS_t + \delta X_t + \varepsilon_t \quad (2)$$

$$Y_t = \varphi + \gamma_1 FTS_t + \delta X_t + \varepsilon_t \quad (3)$$

$$Y_t = \varphi + \gamma_1 INTS_t + \delta X_t + \varepsilon_t \quad (4)$$

To complete the model, variables determining agricultural production, such as the factors of production (land, labor, capital) in South Africa, were included together with other variables that affect agricultural production and productivity such as price changes (inflation), inflation ($Infl$), access to energy (ea), human development index (hdi), and climate change (cc) were included. These additional variables constituted the vector of other critical explanatory variables contained in X. The estimated models then become

$$Y_t = \varphi + \gamma_1 mobs_t + \delta_1 ln_t + \delta_2 lr_t + \delta_3 cap_t + \delta_4 cc_t + \delta_5 hdi_t + \delta_6 ea_t + \delta_7 Infln_t + \varepsilon_t \quad (5)$$

$$Y_t = \varphi + \gamma_1 inu_t + \delta_1 ln_t + \delta_2 lr_t + \delta_3 cap_t + \delta_4 cc_t + \delta_5 hdi_t + \delta_6 ea_t + \delta_7 Infln_t + \varepsilon_t \quad (6)$$

$$Y_t = \varphi + \gamma_1 fts_t + \delta_1 ln_t + \delta_2 lr_t + \delta_3 cap_t + \delta_4 cc_t + \delta_5 hdi_t + \delta_6 ea_t + \delta_7 Infln_t + \varepsilon_t \quad (7)$$

To minimize incidences of heteroscedasticity and multicollinearity in the model and to allow for variable elasticity analysis, the models were transformed (4) into log-log models. The final models for the aggregate and disaggregated components of ICT became

$$lgY_t = \varphi + \gamma_1 lgmobs_t + \delta_1 lgln_t + \delta_2 lglr_t + \delta_3 lgcap_t + \delta_4 lgcc_t + \delta_5 lghdi_t + \delta_6 lgea_t + \delta_7 lginfln_t + \varepsilon_t \quad (8)$$

$$lgY_t = \varphi + \gamma_1 lginu_t + \delta_1 lgln_t + \delta_2 lglr_t + \delta_3 lgcap_t + \delta_4 lgcc_t + \delta_5 lghdi_t + \delta_6 lgea_t + \delta_7 lginfln_t + \varepsilon_t \quad (9)$$

$$lgY_t = \varphi + \gamma_1 lgfts_t + \delta_1 lgln_t + \delta_2 lglr_t + \delta_3 lgcap_t + \delta_4 lgcc_t + \delta_5 lghdi_t + \delta_6 lgea_t + \delta_7 lginfln_t + \varepsilon_t \quad (10)$$

3.2. Econometric Model

The parameter estimates in (8) to (10) above are obtained using the ARDL estimation approach advanced by Pesaran [57,58]. In recent years, co-integration analyses and long-term relationship analyses have shifted towards ARDL over other methods such as vector error correction (VECM) and vector auto-regressive (VAR) approaches. ARDL is the most appropriate for variables integrated at different levels [25,59]. With ARDL, unit root tests are carried out to check if variables are integrated at order 2, I(2), where ARDL will only be inefficient and dropped [43]. Additionally, ARDL tends to be superior for small samples [58]; it lessens the dangers of spurious results according to Ghouse et al. (2018). ARDL simultaneously provides both short- and long-term estimates and executes the co-integration test using the bound-testing approach. ARDL also considers the effects of the lags of both dependent (p) and independent (q) variables on the dependent variable. The ARDL (p, q) model is therefore formulated as follows.

$$y_t = \sum_{j=1}^{p} \lambda_j y_{t-j} + \sum_{j=0}^{q} \delta_j x_{t-j} + \varepsilon_t \quad (11)$$

where y_t is the endogenous variable, x_t represents a $kx1$ vector of exogenous variables, δ_j is a $kx1$ parameter vector, λ_j is the scalar vector, and ε_t is the stochastic error term. In error correction terms, (11) becomes

$$\Delta y_t = \phi y_{t-1} + \beta' x_t + \sum_{j=1}^{p-1} \lambda_j^* \Delta y_{t-j} + \sum_{j=0}^{q-1} \delta_j^* x_{t-j} + \varepsilon_t \quad (12)$$

where $= -1\left[1 - \sum_{j=1}^{p} \lambda_j\right]$; $\beta' = \sum_{j=0}^{q} \delta_j$; $\lambda_j^* = \sum_{m=j+1}^{p} \lambda_m, j = 1,2,\ldots p-1$; $\delta_j^* = \sum_{m=j+1}^{q} \delta_m$, $j = 1,2,\ldots q-1$.

Simplifying (12) gives

$$\Delta y_t = \phi(y_{t-1} + \theta' x_t) + \sum_{j=1}^{p-1} \lambda_j^* \Delta y_{t-j} + \sum_{j=0}^{q-1} \delta_j^* x_{t-j} + \varepsilon_t \quad (13)$$

In (13), $\theta = -\left[\frac{\beta}{\phi}\right]$ shows the long-term elasticities of x_t on y_t. ϕ is the speed of adjustment or error correction term. From the equation, θ measures the speed with which y_t moves back to long-term equilibrium following disturbances in x_t. A significantly negative θ indicates convergence and stability in the long run/steady-state equilibrium [60]. The short-term elasticities of the endogenous and exogenous variables are shown by their respective lagged differences, λ_j^* and δ_j^*, respectively. Applying Equation (13) to the theoretical models (8) to (10) will then transform it into (14) to (16), as below, in line with models specifically for different ICT disaggregated variables (mobile cellphone subscriptions, fixed telephone subscriptions, and internet subscriptions). Two models were therefore estimated per ICT variable in trying to check if the variables that affect agricultural output are the same as those that affect agriculture total factor productivity.

Mobile Cellphone Subscriptions and Agriculture Total Factor Productivity

$$\begin{gathered} lgATFP_t = \phi(\theta_1 lgln_t + \theta_2 lglr_t + \theta_3 lgcap_t + \theta_4 lgcc_t + \theta_5 lghdi_t + \theta_6 lgea_t + \theta_7 lgInfl_t + \theta_8 lgmobs_t) + \\ \sum_{j=1}^{p-1} \lambda_j \Delta lgln_{t-j} + \sum_{j=1}^{q-1} \beta_{1j} \Delta lglr_{t-j} + \sum_{j=1}^{q-1} \beta_{2j} \Delta lgcap_{t-j} + \sum_{j=1}^{q-1} \beta_{3j} \Delta lgcc_{t-j} + \sum_{j=1}^{q-1} \beta_{4j} \Delta lghdi_{t-j} + \\ \sum_{j=1}^{q-1} \beta_{4j} \Delta lgea_{t-j} + \sum_{j=1}^{q-1} \beta_{4j} \Delta lginfln_{t-j} + + \sum_{j=1}^{q-1} \beta_{4j} \Delta lgmobs_{t-j} + \varepsilon_t \end{gathered} \tag{14}$$

Internet Usage and Agriculture Total Factor Productivity

$$\begin{gathered} lgATFP_t = \phi(\theta_1 lgln_t + \theta_2 lglr_t + \theta_3 lgcap_t + \theta_4 lgcc_t + \theta_5 lghdi_t + \theta_6 lgea_t + \theta_7 lgInfl_t + \theta_8 lginu_t) + \\ \sum_{j=1}^{p-1} \lambda_j \Delta lgln_{t-j} + \sum_{j=1}^{q-1} \beta_{1j} \Delta lglr_{t-j} + \sum_{j=1}^{q-1} \beta_{2j} \Delta lgcap_{t-j} + \sum_{j=1}^{q-1} \beta_{3j} \Delta lgcc_{t-j} + \sum_{j=1}^{q-1} \beta_{4j} \Delta lghdi_{t-j} + \\ \sum_{j=1}^{q-1} \beta_{4j} \Delta lgea_{t-j} + \sum_{j=1}^{q-1} \beta_{4j} \Delta lginfln_{t-j} + + \sum_{j=1}^{q-1} \beta_{4j} \Delta lginu_{t-j} + \varepsilon_t \end{gathered} \tag{15}$$

Fixed Telephone Subscriptions and Agriculture Total Factor Productivity Model

$$\begin{gathered} lgATFP_t = \phi(\theta_1 lgln_t + \theta_2 lglr_t + \theta_3 lgcap_t + \theta_4 lgcc_t + \theta_5 lghdi_t + \theta_6 lgea_t + \theta_7 lgInfl_t + \theta_8 lgfts_t) + \\ \sum_{j=1}^{p-1} \lambda_j \Delta lgln_{t-j} + \sum_{j=1}^{q-1} \beta_{1j} \Delta lglr_{t-j} + \sum_{j=1}^{q-1} \beta_{2j} \Delta lgcap_{t-j} + \sum_{j=1}^{q-1} \beta_{3j} \Delta lgcc_{t-j} + \sum_{j=1}^{q-1} \beta_{4j} \Delta lghdi_{t-j} + \\ \sum_{j=1}^{q-1} \beta_{4j} \Delta lgea_{t-j} + \sum_{j=1}^{q-1} \beta_{4j} \Delta lginfln_{t-j} + + \sum_{j=1}^{q-1} \beta_{4j} \Delta lgfts_{t-j} + \varepsilon_t \end{gathered} \tag{16}$$

Mobile Cellphone Subscriptions and Agriculture Output

$$\begin{gathered} lgY_t = \phi(\theta_1 lgln_t + \theta_2 lglr_t + \theta_3 lgcap_t + \theta_4 lgcc_t + \theta_5 lghdi_t + \theta_6 lgea_t + \theta_7 lgInfl_t + \theta_8 lgmobs_t) + \\ \sum_{j=1}^{p-1} \lambda_j \Delta lgln_{t-j} + \sum_{j=1}^{q-1} \beta_{1j} \Delta lglr_{t-j} + \sum_{j=1}^{q-1} \beta_{2j} \Delta lgcap_{t-j} + \sum_{j=1}^{q-1} \beta_{3j} \Delta lgcc_{t-j} + \sum_{j=1}^{q-1} \beta_{4j} \Delta lghdi_{t-j} + \\ \sum_{j=1}^{q-1} \beta_{4j} \Delta lgea_{t-j} + \sum_{j=1}^{q-1} \beta_{4j} \Delta lginfln_{t-j} + + \sum_{j=1}^{q-1} \beta_{4j} \Delta lgmobs_{t-j} + \varepsilon_t \end{gathered} \tag{17}$$

Internet Subscriptions and Output

$$\begin{gathered} lgY_t = \phi(\theta_1 lgln_t + \theta_2 lglr_t + \theta_3 lgcap_t + \theta_4 lgcc_t + \theta_5 lghdi_t + \theta_6 lgea_t + \theta_7 lgInfl_t + \theta_8 lginu_t) + \\ \sum_{j=1}^{p-1} \lambda_j \Delta lgln_{t-j} + \sum_{j=1}^{q-1} \beta_{1j} \Delta lglr_{t-j} + \sum_{j=1}^{q-1} \beta_{2j} \Delta lgcap_{t-j} + \sum_{j=1}^{q-1} \beta_{3j} \Delta lgcc_{t-j} + \sum_{j=1}^{q-1} \beta_{4j} \Delta lghdi_{t-j} + \\ \sum_{j=1}^{q-1} \beta_{4j} \Delta lgea_{t-j} + \sum_{j=1}^{q-1} \beta_{4j} \Delta lginfln_{t-j} + + \sum_{j=1}^{q-1} \beta_{4j} \Delta lginu_{t-j} + \varepsilon_t \end{gathered} \tag{18}$$

Fixed Telephone Subscriptions and Output

$$\begin{gathered} lgY_t = \phi(\theta_1 lgln_t + \theta_2 lglr_t + \theta_3 lgcap_t + \theta_4 lgcc_t + \theta_5 lghdi_t + \theta_6 lgea_t + \theta_7 lgInfl_t + \theta_8 lgfts_t) + \\ \sum_{j=1}^{p-1} \lambda_j \Delta lgln_{t-j} + \sum_{j=1}^{q-1} \beta_{1j} \Delta lglr_{t-j} + \sum_{j=1}^{q-1} \beta_{2j} \Delta lgcap_{t-j} + \sum_{j=1}^{q-1} \beta_{3j} \Delta lgcc_{t-j} + \sum_{j=1}^{q-1} \beta_{4j} \Delta lghdi_{t-j} + \\ \sum_{j=1}^{q-1} \beta_{4j} \Delta lgea_{t-j} + \sum_{j=1}^{q-1} \beta_{4j} \Delta lginfln_{t-j} + + \sum_{j=1}^{q-1} \beta_{4j} \Delta lgfts_{t-j} + \varepsilon_t \end{gathered} \tag{19}$$

In estimating three specified models, (14) to (19), the Akaike information criterion (AIC) was used to determine the optimum lag length. The ARDL bounds test of co-integration uses both the F-statistic and Wald-t tests to check the null hypothesis of no co-integration among the variables. The F and Wald t-statistics are matched with the two sets of critical values of the upper and lower bounds [59]. If the estimated statistics value is higher, then H_0 is rejected; otherwise, it will be accepted. If it lies between the two critical values, the conclusion is indecisive. The results presented include the descriptive statistics, unit root tests, ARDL bounds tests for co-integration, and short-term and long-term results. Variable names, expected signs in the two functions (ATFP models and Output models) and the data sources are presented in Table 1 below.

Table 1. Variables, expected signs and data sources.

Variable Name	Output	ATFP	Data Source
Output (out)	dependent	dependent	Statistics South Africa
ATFP (atfp)	dependent	dependent	USAID
Land (ln)	+ve	+ve	Food and Agriculture Organization (FAO)
Labor (lr)	−ve	+ve	International Labour Organization (ILO)
Capital (cap)	+ve	+ve	Food and Agriculture Organization (FAO)
Climate Change (cc)	−ve	−ve	World Development Indicators
Inflation (infn)	+ve	+ve/−ve	Statistics South Africa
Energy Access (ea)	+ve	+ve	Statistics South Africa
Human Development Index (hdi)	+ve	+ve	World Development Indicators
Mobile Cellphone Subscriptions (mobcs)	+ve	+ve/−ve	International Telecommunications Union
Internet Subscriptions (inu)	+ve	+ve/−ve	International Telecommunications Union
Fixed Telephone Subscriptions (fts)	+ve	+ve/−ve	International Telecommunications Union

4. Results' Presentation and Discussion

4.1. Descriptive Statistics

Table 2 below presents descriptive statistics (mean, standard deviation, skewness, and kurtosis). The mean of agriculture total output value and agriculture total factor productivity were $17,913.057 and 93.852, respectively. The average land, labor, capital, access to energy, human development index, inflation and carbon emissions were 9705 ha, 863.14, R20663, 79.48%, 0.674, 77.06%, and 16710 metric tons of emissions, respectively. On the ICT variables, the mean values for Internet usage, mobile phone subscriptions and fixed telephone subscriptions were 28.26% (Internet penetration), 90.25% (mobile cellphone penetration), and 4286.521. The measures of normality, agriculture total output, land, Internet usage, inflation, and human development index were positively skewed, while agriculture total factor productivity, labor, capital, mobile cellphone subscriptions, fixed telephone subscriptions, climate change, and access to energy were negatively skewed. Looking at the peakness or flatness of the series, the kurtosis results indicated that the normal distribution curves were not perfectly normal, with variables such as agriculture total factor productivity, agricultural output, land, labor, mobile cellphone subscriptions, Internet usage, carbon emissions, inflation, and human development index being less than 3 (platykurtic); meanwhile, capital, fixed telephone subscriptions, and access to energy were greater than 3 (leptokurtic).

Table 2. Descriptive statistics.

	atfp	output	ln	lr	Cap	mobc	inu	fts	cc	infn	hdi	elec
Mean	93.852	17913057	9705	863.1	20663	90.25	28.3	4286521	16710	77.1	0.67	79.5
Std. dev.	13.894	3565021	720	90.48	286.63	61.98	26.9	1001724	564.26	32.2	0.04	7.1
Skewness	−0.124	0.1371	0.29	−0.66	−0.934	−0.142	0.6	−1.312	−0.849	0.43	0.28	−1.6
Kurtosis	2.467	1.9144	1.4	2.87	4.244	1.477	1.6	3.4208	2.854	1.93	1.41	4.8

4.2. Unit Root Tests

The stationarity test results from both the augmented Dickey–Fuller (ADF) and the Phillips–Peron tests, as presented in Table 3 below, indicates that some variables were stationary in their level (capital, agricultural land, mobile cellphone subscriptions, Internet subscriptions, and access to electricity) and some became stationary after first-differencing (agricultural total factor productivity, agricultural output, agricultural labor, agricultural investment measured by machinery, and climate change measured by carbon emissions). No variable became stationary after second differencing, and the sample size was small, justifying the relevance of the ARDL approach.

Table 3. Unit root tests.

	ADF			Phillips–Peron		
Variable	**Level**	**1st Diff**	**Conclusion**	**Level**	**1st Diff**	**Conclusion**
ATFP	1.719	6.238 ***	I(1)	1.689	6.824 ***	I(1)
Output	0.353	4.510 ***	I(1)	0.577	4.433 ***	I(1)
Cap	5.337 ***	-	I(0)	5.340 ***		I(0)
ln	4.140 ***	-	I(0)	4.145 ***		I(0)
lr	1.807	6.727 ***	I(1)	1.802	6.706	I(0)
mobs	3.856 **	-	I(0)	8.153 ***		I(0)
inu	2.891 *	-	I(0)	2.481	2.638 *	I(1)
fts	0.493	3.387 **	I(1)	0.827	3.365	I(1)
cc		3.053 **	I(1)	0.378	2.975 *	I(1)
infln	1.465	3.197 ***	I(1)	1.297	3.177 **	I(1)
ea	2.643 *	-	I(0)	2.687 *		I(0)
hdi	0.114	4.173 ***	I(0)	0.047	4.113 ***	I(1)

***, **, * denote significance at 1%, 5%, and 10%, respectively.

4.3. ARDL Bounds Test for Co-Integration

The bounds' co-integration is sensitive to the number of lags used, hence the researchers applied the lag selection criterion and found the optimum number of lags through the lag order selection statistics. By default, the system chose four as the maximum number of lags and the researchers also chose four as the maximum. The researchers relied on the majority, selected as four, which is also within the yearly data benchmarks. The results are presented in Table 4 below.

Table 4. ARDL bounds test for co-integration.

Model	**F-Statistic**	**F-Critical Values**			**Decision**
ATF Productivity					
Mobile Cellphones (mobs)	4.764 ***	Lower Bound	10%	2.26	Co-integration
Internet (inu)	9.865 ***	Upper Bound	10%	3.35	Co-integration
Fixed Telephones (fts)	3.167	Upper Bound	5%	3.79	Inconclusive
Output					
Mobile Cellphones (mobs)	19.453 ***	Lower Bound	5%	2.62	Co-integration
Internet (inu)	9.115 ***	Lower Bound	1%	3.41	Co-integration
Fixed Telephones (fts)	7.444 ***	Upper Bound	1%	4.68	Co-integration

***, **, * denotes significance at 1%, 5%, and 10%, respectively.

After applying the lag selection criterion, the bounds test for co-integration was carried out using STATA 14 to examine the number of co-integrating equations between the variables. A co-integration equation exists at a point where the calculated F-statistic is greater than the critical value for the upper bound I (1). This means that there is a long-term relationship and vice versa. For the models estimated, five of them (productivity models (mobile cellphone subscriptions and Internet subscriptions) and the agricultural output functions (mobile cellphone subscriptions, Internet subscriptions, and fixed telephone subscriptions models)) indicated that there was co-integration because the F-statistic was found to be greater than the critical values at all levels of significance. However, only the fixed telephone subscriptions model was inconclusive because the F-statistic was found to be in between the critical values, all at a 5% level of significance. This therefore indicated that both the long-term and short-term estimates of the relationship can be relied upon. From the five models that exhibited co-integration, the null hypothesis of no long-term relationship can be rejected, while the fixed telecommunications model under the productivity model was inconclusive, meaning the null hypothesis cannot be accepted/rejected; thus, the long-term relationship was also estimated. After the ARDL bounds test for co-integration, the ARDL model was estimated, and the results were broken down for presentation in the following Table 5 (long-term results) and Table 6 (short-term results).

Table 5. Long-term results for the ICT models.

Long-Term and Short-Term Results						
	Agriculture Total Factor Productivity			Output		
Variables	**Mobcs (1)**	**Inu (2)**	**Fts (3)**	**Mobcs (4)**	**Inu (5)**	**Fts (6)**
ECT	−0.535 **	−0.788 ***	−0.353 ***	−1.281 ***	−0.862 **	−0.706 **
	(0.185)	(0.019)	(0.213)	(0.234)	(0.269)	(0.154)
Land (ln)	0.294 **	0.460	0.105	0.890 ***	0.194 **	−0.398 **
	(0.051)	(0.303)	(0.105)	(0.145)	(0.011)	(0.398)
Labor (lr)	−0.070	0.367 *	−0.070	−0.485 **	−0.143	0.073
	(0.154)	(0.156)	(0.155)	(0.163)	(0.087)	(0.154)
Capital (cap)	0.164	0.714 *	0.0356	−0.535 *	0.294 ***	−0.143
	(0.131)	(0.362)	(0.362)	(0.186)	(0.051)	(0.086)
Climate change (cc)	−0.070 *	−0.346 **	−0.194	−0.002 **	−0.015 *	−0.010
	0.086	(0.134)	(0.192)	(0.0006)	(0.005)	(0.209)
HDI (hdi)	0.029 ***	0.022 **	0.169	0.890 ***	−0.020 **	0.088
	(0.003)	(0.003)	(0.086)	(0.146)	(0.004)	(0.097)
Energy access (ea)	−0.023	−0.322 **	0.019	0.164	0.101	−0.013 **
	(0.073)	(0.113)	(0.012)	(0.131)	(0.102)	(0.004)
Inflation (infn)	−0.154 **	−0.575	−0.460	0.341 **	−0.029 ***	−0.008
	(0.065)	(0.461)	(0.303)	(0.152)	(0.003)	(0.007)
MOBS (mobs)	0.027 ***			0.008 **		
	(0.005)			(0.003)		
INU (inu)		0.505 ***			0.346 **	
		(0.145)			(0.134)	
FTS (fts)			0.022 **			−0.575
			(0.003)			(0.461)
R2	0.931	0.962	0.893	0.940	0.996	0.926
Adjusted R2	0.872	0.91	0.837	0.881	0.972	0.865

Table 5. *Cont.*

Long-Term and Short-Term Results						
	Agriculture Total Factor Productivity			Output		
Variables	**Mobcs (1)**	**Inu (2)**	**Fts (3)**	**Mobcs (4)**	**Inu (5)**	**Fts (6)**
Diagnostics						
Durban–Watson	2.03	3.123	2.167	2.425	3.059	3.671
LM_Arch χ^2	[0.134]	[0.138]	[0.176]	[0.078]	[0.395]	[0.276]
B_Pagan χ^2	[0.178]	[0.705]	[0.629]	[0.254]	[0.867]	[0.914]
Ramsey test	[0.303]	[0.103]	[0.295]	[0.355]	[0.464]	[0.366]
Skewness χ^2	[0.461]	[0.959]	[0.799]	[0.461]	[0.873]	[0.784]

In parenthesis () are standard errors and ***, **, * denote significance at 1%, 5%, and 10%, respectively.

Table 6. ARDL short-term results.

ARDL Short-Term Results							
		Agriculture Total Factor Productivity			Output Models		
	Lags	**Mobcs (1)**	**Inu (2)**	**Fts (3)**	**Mobcs (1)**	**Inu (2)**	**Fts (3)**
mobcs	D1.	0.114			−0.670 ***		
		(0.080)			(0.189)		
	LD.	0.154 **			0.789 **		
		(0.065)			(0.258)		
	L2D.	−0.117 *			0.7553		
		(0.057)			(0.305)		
	L3D.	0.115					
		(0.065)					
inu	D.		0.284 **			0.1212	
			(0.077)			(0.162)	
	LD.		−0.023			−0.376	
			(0.073)			(0.356)	
	L2D.		−0.322 **			2.1991 **	
			(0.113)			(0.702)	
fts	D.			−0.023			−0.296 *
				(0.073)			(0.115)
	LD.			0.115			
				(0.065)			
ln	D.	0.157	1.079	0.088	0.308 *	−0.294	0.214
		(0.131)	(0.147)	(0.097)	(0.127)	(0.215)	(0.120)
	LD.		1.497 ***			2.198 ***	
			(0.286)			(0.702)	
lr	D.	0.149	−0.013 *	0.030	0.197	0.009 *	−0.116
		(0.233)	(0.004)	(0.159)	(0.219)	(0.003)	(0.162)
	LD.	−0.010		0.159	0.492*		0.409
		(0.206)		(0.122)	(0.212)		(0.216)

Table 6. *Cont.*

				ARDL Short-Term Results			
		Agriculture Total Factor Productivity			**Output Models**		
	Lags	**Mobcs (1)**	**Inu (2)**	**Fts (3)**	**Mobcs (1)**	**Inu (2)**	**Fts (3)**
cap	D.	0.092	2.9526 *	−1.608 *	0.009	0.069	−0.7061
		(0.272)	(1.2032)	(0.767)	(0.179)	(0.286)	(1.741)
	LD.	−0.526*		−0.030		0.814**	0.092
		(0.237)		(0.113)		(0.202)	(0.272)
	L2D.			0.054			−0.304
				(0.152)			(0.174)
cc	D.	−0.444 **	−0.116	−0.409	−0.336 **	0.016	−0.007
		(0.117)	(0.162)	(0.216)	(0.087)	(0.007)	(−0.004)
	LD.		−0.444 **		0.197	−0.013 *	
			(0.117)		(0.219)	(0.004)	
	L2D.					−1.94 **	
						(0.63)	
hdi	D.	1.673 ***	0.8 ***	0.165 *	0.0003	0.093	−0.007
		(0.199)	(0.162)	(0.068)	(0.006)	(0.199)	(−0.004)
	LD.	0.001		0.030	0.005	1.432 **	
		(0.004)		(0.159)	(0.005)	(0.426)	
	L2D.				0.308 *		
					(0.127)		
ea	D.	0.383 **	−0.781	0.7652	−0.042	2.125	0.6441 *
		(0.016)	(0.393)	(0.7323)	(0.126)	(0.596)	(0.277)
	LD.	0.0695	4.279 ***		0.698 **	−1.271 *	−0.181
		(0.289)	(0.048)		(0.009)	(0.035)	(0.294)
infln	D.	−0.031 **	0.0695	−0.181	−0.042	−0.184 *	−0.003 **
		(0.008)	(0.286)	(0.293)	(0.125)	(0.294)	(0.118)
	LD.	−0.409	−4.325 *		0.699 **	−0.182	0.713 ***
		(0.195)	(1.823)		(0.009)	(0.294)	(0.01)
	L2D.	0.190 *				−0.346 **	−0.042
		(0.027)				(0.017)	(0.126)
Constant		4.765 ***	7.267 ***	7.906 **	5.203 **	11.29 ***	3.906 **
		(1.359)	(1.538)	(1.617)	(1.912)	(1.938)	(1.117)

In parenthesis () are standard errors and ***, **, * denote significance at 1%, 5%, and 10%, respectively.

4.4. Long-Run Results

The error correction terms (ECT) for the agriculture total factor productivity and the agricultural production models were found to be negative (−0.535, −0.7881, and −0.3527 and −1.2811, −0.8619, and −0.7064) and statistically significant at 1% and 5%. This signifies high speed of adjustment to agriculture total productivity and agricultural output long-term equilibria following dynamics in the explanatory variables (53.5%, 78.8% and 35.3% for the agriculture total factor productivity models and 128.11%, 86.19% and 70.64% for the output models). The high speed of long-term adjustment confirms the magnitude of the influence of the explanatory variables on the explained variables (agriculture total factor productivity and agricultural output), thereby endorsing long-term association between the explanatory variables and the independent variables. The models' combined variables' explanatory power was also found to be meaningfully higher, as indicated by the higher R-squared and adjusted R-squared values.

For the long-term results presented in Table 5, land was positive and statistically significant in affecting agriculture total factor productivity change in the mobile cellphone subscription model at a 1% level of significance; meanwhile, the Internet subscriptions and fixed telephone subscriptions models were insignificant, despite having positive coefficients. Increasing land in the output models resulted in growth in production. Like any factor of production, land has a greater increasing effect on output than productivity in the long run. Labor was found to be positive and statistically significant in the Internet usage model, meaning that Internet use improves labor productivity, which in turn results in growth in ATFP (a unit increase in labor resulted in a 0.367% increase in ATFP in the long run). Meanwhile, for the mobile phone and fixed telephone subscriptions models, labor was found to be negative though statistically insignificant. In terms of output, labor was found to be significant in the mobile cellphone subscriptions (mobcs) model but had no effect on the fixed telephone subscriptions (fts) and the Internet usage (inu) models in the long run. Capital had a positive and negative statistically significant impact on output on the inu and mobcs models, respectively, but had an insignificant effect on the fts model. However, capital was found to affect productivity positively under the inu and fts models, at a 10% level of significance, but had no impact under the mobcs model. Capital was therefore found to have more impact on output than on productivity in the long run.

Climate change negatively affects agricultural output in the mobcs and inu models. A unit increase in carbon emissions resulted in a 0.2% and 0.15% decrease in agricultural output, while it also had a negative and statistically significant effect on productivity (0.07% and 0.36% under the mobcs and inu functions). Climate change, therefore, was found to have more impact on productivity than output in the long run, confirming the findings of a previous study [43,61,62]. Human development index was found to have a positive and statistically significant impact on agricultural output in the mobcs model but a negative and statistically significant impact on the inu model (a percentage increase in HDI resulted in a 0.89% increase in output in the mobcs long-term model but a 0.02% decrease in output in the inu model). Simply put, the human development index reduces production but increases productivity in the long run in the inu model, while it increases both productivity and output growth in the mobcs model in the long run. Energy access was found to positively affect agricultural production under the fts model (a percentage increase in access to energy resulted in a 0.013% increase in agricultural output) and positively affected productivity under in the inu model (a percentage increase in access to energy resulted in a 0.322% increase in ATFP in the long run). Inflation was found to negatively affect agricultural output in the mobcs and inu models, while it affected productivity only via the mobcs model. Inflation therefore affects agricultural production (output) more than productivity in the long run.

On the ICT variables, mobile cellphone subscriptions were found to have a positive and statistically significant impact on both agricultural output and ATFP in the long run. The findings generally conform with those of previous studies [12,33,48,53]. A percentage increase in mobile cellphone subscriptions resulted in a 0.008% increase in output and a 0.027% increase in ATFP in the long run. This means mobile cellphone subscriptions affect agriculture total factor productivity more than output in general. Internet usage was found to have a statistically and significant effect on agricultural output (a percentage increase in Internet usage resulted in 0.346% growth in agricultural output at a 5% level of significance) and ATFP (a percentage increase in Internet usage resulted in a 0.505% growth in ATFP change at a 1% level of significance). The long-term results therefore conform with those of previous findings [12]. Despite positively affecting both output and productivity, the Internet (inu) proved to have more impact on ATFP. Internet usage (inu) therefore affects total factor productivity more than ATFP, even if there is no meaningful growth in output in the long run. Fixed telephone subscriptions were found to only affect ATFP in the long run, while we found no impact on agricultural output. This may be through the interaction with other variables such as the Internet, given that fixed broadband is usually cheaper than mobile broadband; thus, individuals with fixed telephone lines tend to enjoy more cheap and efficient Internet connectivity than those depending on mobile broadband in South Africa.

4.5. Diagnostics

Diagnostic test results are presented under the long-term estimated results. To establish the soundness of the estimated model, several diagnostic tests, namely the Jarque–Bera normality test, the Breusch–Godfrey serial correlation LM test, the Ramsey reset for model specification, and the ARCH test for heteroskedasticity, were carried out. The reported statistic of the Jarque–Bera test for normality rejects the null hypothesis that the estimated residual series are not normally distributed for all six models. Serial correlation is rejected as indicated by the LM statistics. The ARCH test for heteroskedasticity for all the six equations shows that the residuals do not suffer from heteroskedasticity. Finally, the reset test indicates that the models were stable. For model stability, the Cusum test was used to check if the coefficients diverge in ways that were not forecasted by the regression model. From the six models used, the Cusum squared values were found to be within the Cusum 5% confidence bands. Consequently, the null hypothesis of model instability is rejected for all the six models, hence the results from the six models are considered stable.

4.6. Short-Term Results

Looking at the short-term results, the second and third lags of mobile cellphone subscriptions affect ATFP positively and negatively, respectively, in the short term (all things being equal, a percentage point increase in mobcs resulted in a 0.154% increase in ATFP and a 0.117% decrease in ATFP, respectively, conforming with the short-term findings of other previous studies [29,50] and contrary to Aminou et al. [44]). However, in the short term, on agricultural output, the first and second lags affect agricultural output negatively and positively, contrary to other studies [24,48,63] and conforming with other studies [40], respectively (a percentage increase in mobcs resulted in a 0.67% decrease and a 0.789% increase in agricultural output, respectively). Internet usage proved to positively affect agricultural output in the short term through the third lag, where a percentage increase in Internet usage resulted in a 2.199% increase in agricultural output in the short term, as in the findings of Ejemeyovwi et al. [50]. On ATFP, the first lag of Internet usage affects ATFP positively, as in Khan et al. (2022), while the third lag affects ATFP negatively both at a 5% level of significance (a percentage increase in Internet usage resulted in a 0.284% increase and a 0.322% decrease in ATFP, respectively) in the short run. On the other hand, fixed telephone subscriptions negatively affect agricultural output through the first lag at a 10% level of significance (a percentage increase in fixed telephone subscriptions resulted in a 0.296% reduction in agricultural output).

For conventional factors of production such as land, in the Internet models of ATFP and agricultural output, they affected ATFP and output positively (through the second lag in the short run at a 5% level of statistical significance). This means increasing land size results in short-term growth in output and ATFP (a percentage increase in land resulted in a 2.198% increase in agricultural output and a 1.497% increase in ATFP). Growth in labor was found to affect ATFP negatively in the short run using the Internet model of both ATFP and agriculture output. Through the second lag in the mobile cellphone subscriptions model, capital was found to negatively affect ATFP at a 10% level of significance. Through the first lag in the Internet usage model at a 10% level of significance, capital affected ATFP positively; it affected it negatively using the fixed telephone subscriptions model. Finally, capital positively affected agricultural output (a percentage increase in capital resulted in a 0.8823% in output in the short run).

Climate change has emerged as a variable that torments rural and farming and non-farming economic activities. In this study, in the mobile cellphone subscriptions model, climate change was found to negatively affect ATFP in the short run (a percentage increase in carbon emissions resulted in a decrease in ATFP at a 10% level significance). Climate change affects output negatively (a percentage change in climate change was associated with a 0.336% decrease in agricultural output in the mobile cellphone subscriptions model). Likewise, in the internet usage model, climate change affected agricultural output negatively through the second and third lags in the short run.

In the short run, human development index generally affects ATFP positively when evaluated in the three models used (mobile cellphone and fixed telephone subscriptions and Internet usage at 1%, 10%, and 1% levels of significance, respectively, through the first lag. For the mobile cellphone subscriptions model, a percentage increase in human development was associated with a 1.673% growth in ATFP. A percentage increase in human development, measured through an increase in the Internet usage model, resulted in 0.8% growth in ATFP. A percentage increase in the human development index via the fixed telephone subscriptions model resulted in 0.165% growth in ATFP in the short run. For the output models, the human development index also affects total agricultural production positively. This is evidenced through the third lag of human development index in the mobile cellphone subscriptions model, where a percentage increase in human development index resulted in a 0.308% increase in agricultural output, and through the second lag of the Internet usage function, where a percentage increase in human development index was associated with a 1.432% growth in agricultural output in the short run.

Energy access is a critical component when it comes to the digitalization process. The first lag of access to energy was found to positively affect ATFP through the mobile cellphone subscriptions model, where a percentage increase in energy access was associated with a 0.383% change in ATFP at a 10% level of significance in the short run. Additionally, the second lag of access to energy positively and significantly affects ATFP (a percentage increase in energy access was associated with 4.279% ATFP growth through the Internet usage model). On agricultural output, the second lag of access to energy was positively associated with 0.698% growth in agricultural output through the mobile cellphone subscriptions model in the short run. On output, the second lag of access to energy negatively affects agricultural output in the short run (a percentage increase in access to energy was associated with a 1.271% growth in agricultural production) through the Internet usage model. Likewise, through the fixed telephone subscriptions model, access to energy positively affects agricultural output in the short run (a percentage increase in access to energy was associated with a 0.644% increase in output).

Through the various models used, inflation proved to have mixed impacts on agricultural development in South Africa. Using the mobile cellphone subscriptions model, a 1% increase in inflation affected ATFP through the first and third lags (a 1% increase in inflation was associated with a −0.031% and 0.190% decrease and increase in ATFP, respectively) in the short run. A percentage increase in inflation also affected ATFP negatively (being associated with a 4.325% decrease in ATFP) through the second lag at a 5% level of significance via the Internet usage model. On agricultural output functions, the second lag of inflation positively affected agricultural output, where a percentage increase in inflation resulted in a 0.699% increase in agricultural output in the short run using the mobile cellphone subscriptions model. Through the first and third lags of inflation, a percentage increase in inflation was associated with 0.184% and 0.346% (at 10% and 5% levels of significance) decreases in agricultural output in the short run. For the fixed telephone subscriptions model, inflation had a mixed impact on output. The first lag of inflation had a negative impact on agricultural output (a percentage increase in inflation triggered a 0.003% decrease in agricultural output in the short run), while the second lag had a positive impact on output (a percentage increase in inflation resulted in a 0.713% increase in agricultural output in the short run), all things being equal.

5. Conclusions and Policy Recommendations

This research investigates the impact of Information and Communication Technology and its impact on agricultural development (through agricultural output and productivity) in South Africa. From the findings of the study, generally, ICTs have critical, positive and significant roles to play in the development of the South African agriculture sector. Our findings revealed that ICTs such as mobile phones and Internet usage are the main drivers of agricultural output and ATFP growth in South Africa in both the short run and long run. As in previous studies [12,53,64], mobile phone subscriptions and Internet usage have proved to have more impact on agricultural development than fixed telephone line subscriptions in South Africa. This may be because fixed telephone subscriptions tend to be overshadowed by mobile cellphone subscriptions and the Internet; thus, they have a reduced impact on agricultural development, and this can be explained by the fact that mobile phones used to be a substitute for fixed telephones but are fast becoming a compliment to them, wherein fixed broadband can be used on mobile phones at work places and even at home, hence the significant long-term positive effect. Concerning the conventional factors of production, generally, land, capital, and labor were found to have a positive impact on agricultural development both in the short run and the long run, meaning making more land available for agriculture will result in the development of the South African agriculture sector though more investment in agriculture capital (and therefore more impact on agriculture productivity than on output growth).

Findings from the additional variables like climate change and inflation revealed generally negative effects on agricultural development in South Africa. On the other hand, human development index and access to energy (electricity) have positive impacts on agricultural development in South Africa both in the short run and long run, and this can be attributed to the fact that they act as compliments to mobile cellphone subscriptions and Internet usage (when there is no electricity, mobile networks tend to be weak or unavailable, meaning limited access; moreover, effective utilization of mobile phones and the Internet is complimented by education, income, and health, as these are part of the human development index).

The results of this study revealed several important implications for policy makers: as generally, mobile cellphones and the Internet have the effect of increasing agricultural development (agricultural production and productivity), investment in ICT infrastructure should be further prioritized in order to maximize the benefits from mobile phone subscriptions and Internet usage in the agricultural sector. Investment in ICT infrastructure may trigger more collaborations in developing tools, instruments, and applications for use by farmers, including in the remote areas of South Africa where agriculture is the main source of rural income and the main provider of small-scale farm and non-farm rural enterprises. Players in the ICT industry will have to prioritize the promotion of mobile and Internet technologies in trying to accelerate digitization of the agriculture sector in South Africa. This may be, for example, through revamping fixed telephone lines to enhance cheaper ways of accessing and using ICT (through enhanced affordability) where mobile telecommunication is more expensive than fixed-line telecommunications. This will enhance efficient and affordable access to the Internet through fixed broadband lines, and this is evidenced by the positive long-term effect of fixed telephone subscriptions on agricultural development in South Africa. Farmers should have access to more mobile applications if they happen to be cheaper. Policy initiatives may also target agriculture-based ICT innovations so that there will be more applications and incentives that promote agricultural production and productivity growth. The agriculture institutes of higher and tertiary learning institutions should heavily invest in research and innovation to promote the development and innovation of region-/area-specific agricultural ICT needs.

Additional policy recommendations may be derived from the other control variables included in the estimations. These may include making more land available for agriculture either through resettlement exercises and sourcing more funds through climate financing to increase government involvement in fighting climate change together with prioritizing non-governmental organizations (NGOs) that target climate change so as to reduce the devastating impact of climate change, for example, by promoting the adoption climate-smart or precision agriculture. They may also include increasing health and education funding so as to improve the human development index and targeting stability in prices and promoting the use of other green/clean sources of energy (like solar) to supplement hydroelectricity, which is proving to be inadequate and causing a lot of load-shedding, thereby limiting the effectiveness of ICT use. The government of South Africa should also partner with NGOs to promote the utilization of ICTs since the effectiveness of ICTs in agricultural development depends more on utilization than general subscriptions, as used as proxies in this study; primary data-based studies or case studies may speak more to the effectiveness of ICTs on agricultural production and productivity growth. Given the above, we also recommend the development of ICT tools that can be introduced to farmers and impact evaluation studies rather than simple adoption/subscription numbers, as this may have limited the current study. Additionally, case studies and or impact evaluation studies of the above nature may help by shedding more light on the extent of ICTs' impact on agricultural production and productivity growth; this helps both small-scale/smallholder farmers and large-scale commercial farmers.

Many studies seek to ascertain the mediating role of ICT in partial productivity indices in order to know whether ICTs augment capital, land, or labor and to what extent ICTs augment the conventional factors of production together with the combined effects of ICT variables; this is because they sometimes seem to augment and enhance each other. For instance, fixed telephone lines and Internet usage/access or mobile cellphone subscriptions and Internet usage may have combined effects on agricultural development. There is a need to assess the mediating role of ICT in agricultural development. Additionally, there are many additional variables, such as government expenditure on agriculture, agriculture subsidies, exchange rates, agriculture trade and agriculture credit (exports and imports), natural disasters, and many others that were excluded from the current study due to data availability and gaps.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/agriculture14081253/s1.

Author Contributions: S.M. (conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, visualization). Y.S.H. (supervision, validation, editing, visualization, writing—review and editing). All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the Small-Scale Agribusiness Non-Farm Enterprises research niche.

Institutional Review Board Statement: Not applicable.

Data Availability Statement: Data supporting this study are included within the article's Supporting Materials.

Acknowledgments: We thank the Small-Scale Agribusiness Rural Non-Farm Enterprises research niche for facilitating and funding the APCs of the study.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Mdoda, L.; Mdiya, L. Factors affecting the using information and communication technologies (ICTs) by livestock farmers in the Eastern Cape province. *Cogent Soc. Sci.* **2022**, *8*, 2026017. [CrossRef]
2. David, O.; Grobler, W. Agricultural Production in South Africa: Information and Communication Technology (Ict) Spillover. *Int. J. Ebus. Egov. Stud.* **2019**, *11*, 166–190. [CrossRef]
3. Mthiyane, D.B.; Wissink, H.; Chiwawa, N. The impact of rural-urban migration in South Africa: A case of KwaDukuza municipality. *J. Local Gov. Res. Innov.* **2022**, *3*, a56. [CrossRef]

4. United Nations, Department of Economic and Social Affairs, Population Division (2019). World Urbanization Prospects: The 2018 Revision (ST/ESA/SER.A/420). United Nations: New York, NY, USA. Available online: http://creativecommons.org/licenses/by/3.0/igo/ (accessed on 15 July 2024).
5. International Telecommunication Union. *Measuring Digital Development. Facts and Figures 2022*; International Telecommunication Union: Geneva, Switzerland, 2022; Available online: https://www.itu.int/en/ITU-D/Statistics/Documents/facts/FactsFigures2020.pdf (accessed on 18 October 2023).
6. 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]
7. Economic Review of the South African Agriculture 2020/21, Department of Agriculture, Land Reform and Rural Development. Available online: https://www.dalrrd.gov.za/phocadownloadpap/Statistics_and_Economic_Analysis/Statistical_Information/Economic%20Review%202020.pdf (accessed on 17 February 2024).
8. Raheem, D.; Dayoub, M.; Birech, R.; Nakiyemba, A. The Contribution of Cereal Grains to Food Security and Sustainability in Africa: Potential Application of UAV in Ghana, Nigeria, Uganda, and Namibia. *Urban Sci.* **2021**, *5*, 8. [CrossRef]
9. Kante, M.; Oboko, R.; Chepken, C. Factors affecting the use of ICT s on agricultural input information by farmers in developing countries. *AIMS Agric. Food* **2016**, *1*, 315–329. [CrossRef]
10. Bahrini, R.; Qaffas, A.A. Impact of Information and Communication Technology on Economic Growth: Evidence from Developing Countries. *Economies* **2019**, *7*, 21. [CrossRef]
11. ITU. *World Telecommunication/ICT Indicators Database 2022*; International Telecommunication Union: Geneva, Switzerland, 2022.
12. 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]
13. FAO. *World Livestock: Transforming the Livestock Sector through the Sustainable Development Goals*; FAO: Rome, Italy, 2017; 222p. [CrossRef]
14. Kim, J.; Park, J.C.; Komarek, T. The impact of Mobile ICT on national productivity in developed and developing countries. *Inf. Manag.* **2021**, *58*, 103442. [CrossRef]
15. Lee, S.H.; Levendis, J.; Gutierrez, L. Telecommunications and Economic Growth: An Empirical Analysis of Sub-Saharan Africa. *Appl. Econ.* **2012**, *44*, 461–469. [CrossRef]
16. Pradhan, R.P.; Mallik, G.; Bagchi, T.P. Information communication technology (ICT) infrastructure and economic growth A causality evinced by cross-country panel data. *IIMB Manag. Rev.* **2018**, *30*, 91–103. [CrossRef]
17. Chavula, H.K. The role of ICTs in agricultural production in Africa. *J. Dev. Agric. Econ.* **2014**, *6*, 279–289. [CrossRef]
18. Kabbiri, R.; Dora, M.; Kumar, V.; Elepu, G.; Gellynck, X. Mobile phone adoption in agrifood sector: Are farmers in Sub-Saharan Africa connected? *Technol. Forecast. Soc. Chang.* **2018**, *131*, 253–261. [CrossRef]
19. Olaniyi, E. Digital Agriculture: Mobile Phones, Internet Agricultural Development in Africa. MPRA Paper No. 90359. 2018. Available online: https://mpra.ub.uni-muenchen.de/90359/ (accessed on 13 April 2023).
20. Quandt, A.; Salerno, J.D.; Neff, J.C.; Baird, T.D.; Herrick, J.E.; McCabe, J.T. Mobile phone use is associated with higher smallholder agricultural productivity in Tanzania, East Africa. *PLoS ONE* **2020**, *15*, e0237337. [CrossRef]
21. Shiferaw, B.; Kebede, T.; Kassie, M.; Fisher, M. Market imperfections, access to information and technology adoption in Uganda: Challenges of overcoming multiple constraints. *Agric. Econ.* **2015**, *46*, 475–488. [CrossRef]
22. Latif, Z.; Latif, S.; Liu, X.; Pathan, Z.H.; Salam, S.; Zeng, J. The dynamics of ICT, foreign direct investment, globalization, and economic growth: Panel estimation robust to heterogeneity and cross-sectional dependence. *Telemat. Inform.* **2018**, *35*, 318–328. [CrossRef]
23. Wolfert, S.; Ge, L.; Verdouw, C.; Bogaardt, M.J. Big data in smart farming—A review. *Agric. Syst.* **2017**, *153*, 69–80. [CrossRef]
24. Olaniyi, O.A.; Ismaila, K.O. Information and communication technologies (ICTs) usage and household food security status of maize crop farmers in Ondo State, Nigeria: Implication for sustainable development. *Libr. Philos. Pract. (E-J.)* **2016**, 1446. Available online: http://digitalcommons.unl.edu/libphilprac/1446 (accessed on 23 September 2023).
25. Nkoro, E.; Uko, A.K. Autoregressive distributed lag (ARDL) cointegration technique: Application and interpretation. *J. Stat. Econom. Methods* **2016**, *5*, 63–91.
26. Leng, C.; Ma, W.; Tang, J.; Zhu, Z. ICT adoption and income diversification among rural households in China. *Appl. Econ.* **2020**, *52*, 3614–3628. [CrossRef]
27. Heeks, R. Future Priorities for Development Informatics Research from the Post-2015 Development Agenda. In *Development Informatics Working Paper 57*; Centre for Development Informatics, University of Manchester: Manchester, UK, 2014; Available online: https://www.researchgate.net/publication/334612966_Future_Priorities_for_Development_Informatics_Research_from_the_Post-2015_Development_Agenda (accessed on 17 February 2024).
28. OECD. OECD and the Sustainable Development Goals: Delivering on Universal Goals and Targets. 2017. Available online: http://www.oecd.org/development/sustainable-development-goals.htm (accessed on 15 April 2023).
29. World Bank. *World Bank Development Report: Digital Dividends*; World Bank Group: Washington, DC, USA, 2017.
30. Sunge, R.; Makamba, B.S. Testing the Quantity Theory of Money in Zimbabwe under the Multiple Currency Regime: An ARDL Bound Testing Approach. *Afr. J. Econ. Rev.* **2020**, *8*, 65–88.
31. Haile, G.G.; Tang, Q.; Sun, S.; Huang, Z.; Zhang, X.; Liu, X. Droughts in East Africa: Causes, impacts and resilience. *Earth-Sci. Rev.* **2019**, *193*, 146–161. [CrossRef]

32. Ramzan, S.A.; Raza, M.; Usman, G.D.; Sharma, H.A. Iqbal Environmental cost of non-renewable energy and economic progress: Do ICT and financial development mitigate some burden? *J. Clean. Prod.* **2022**, *333*, 130066. [CrossRef]
33. Khan, N.; Ray, R.L.; Kassem, H.S.; Zhang, S. Mobile Internet Technology Adoption for Sustainable Agriculture: Evidence from Wheat Farmers. *Appl. Sci.* **2022**, *12*, 4902. [CrossRef]
34. Aghaei, M.; Rezagholizadeh, M. The Impact of Information and Communication Technology (ICT) on Economic Growth in the OIC Countries. *Econ. Environ. Stud.* **2017**, *17*, 255–276. [CrossRef]
35. Sinha, A.; Sengupta, T.; Alvarado, R. Interplay between technological innovation and environmental quality: Formulating the SDG policies for next 11 economies. *J. Clean. Prod.* **2020**, *242*, 118549. [CrossRef]
36. Hudson, H.E.; Leclair, M.; Pelletier, B.; Sullivan, B. Using radio and interactive ICTs to improve food security among smallholder farmers in Sub-Saharan Africa. *Telecommun. Policy* **2017**, *41*, 670–684. [CrossRef]
37. Mafizur, M.; Arifeen, S.; Mamun, K. The effects of telephone infrastructure on farmers' agricultural outputs in China. *Inf. Econ. Policy* **2017**, *41*, 88–95. [CrossRef]
38. Suresh, K.; Khanal, U.; Wilson, C.; Managi, S.; Quayle, A.; Santhirakumar, S. An economic analysis of agricultural adaptation to climate change impacts in Sri Lanka: An endogenous switching regression analysis. *Land Use Pol.* **2021**, *109*, 105601. [CrossRef]
39. Malthus, T.R. An Essay on the Principle of Population, as It Affects the Future Improvement of Society with Remarks on the Speculations of Mr. Godwin, M. Condorcet, and Other Writers. London. 1798. Available online: http://www.esp.org/books/malthus/population/malthus.pdf (accessed on 16 June 2023).
40. Chandio, A.A.; Sethi, N.; Dash, D.P.; Usman, M. Towards sustainable food production: What role ICT and technological development can play for cereal production in Asian−7 countries? *Comput. Electron. Agric.* **2022**, *202*, 107368. [CrossRef]
41. Karanasios, S.; Slavova, M. Understanding the Impacts of Mobile Technology on Smallholder Agriculture. In *Digital Technologies for Agricultural and Rural Development in the Global South*; CAB International: Wallingford, UK, 2018; p. 111.
42. Lio, M.; Liu, M.C. ICT and agricultural productivity: Evidence from cross-country data. *Agric. Econ.* **2006**, *34*, 221–228. [CrossRef]
43. Suroso, A.I.; Fahmi, I.; Tandra, H. The Role of Internet on Agricultural Sector Performance in Global World. *Sustainability* **2022**, *14*, 12266. [CrossRef]
44. Aminou, F.A.; Houensou, D.A.; Hekponhoue, S. Effect of Mobile Phone Ownership on Agricultural Productivity in Benin: The Case of Maize Farmers. *J. Econ. Dev. Stud.* **2018**, *6*, 77–88. [CrossRef]
45. Chikuni, T.; Kilima, F.T. Smallholder farmers' market participation and mobile phone-based market information services in Lilongwe, Malawi. *Electron. J. Inf. Syst. Dev. Ctries.* **2019**, *85*, e12097. [CrossRef]
46. Hoang, H.G. Determinants of the adoption of mobile phones for fruit marketing by Vietnamese farmers. *World Dev. Perspect.* **2020**, *2020*, 100178. [CrossRef]
47. Hung, H.G. Adoption of Mobile Phone for Marketing of Cereals by Smallholder Farmers in Quang Dien District of Vietnam. *J. Agric. Ext.* **2020**, *24*, 106–117. [CrossRef]
48. Mwalupaso, G.E.; Wang, S.; Rahman, S.; Alavo, E.J.-P.; Tian, X. Agricultural Informatization and Technical Efficiency in Maize Production in Zambia. *Sustainability* **2019**, *11*, 2451. [CrossRef]
49. Sekabira, H.; Qaim, M. Can mobile phones improve gender equality and nutrition? Panel data evidence form farm households in Uganda. *Food Policy* **2017**, *73*, 95–103. [CrossRef]
50. Ejemeyovwi, J.O.; Osabuohien, E.S. ICT Adoption and Inclusive Growth in West Africa: Dynamic Panel Data Analysis. Unpublished. Master's Thesis, Department of Economics and Development Studies, Covenant University, Ota, Nigeria, 2017.
51. Jahanger, A.; Usman, M.; Murshed, M.; Mahmood, H.; Balsalobre-Lorente, D. The linkages between natural resources, human capital, globalization, economic growth, financial development, and ecological footprint: The moderating role of technological innovations. *Resour. Policy* **2022**, *76*, 102569. [CrossRef]
52. USAID. Technology Division Innovation, Technology, and Research Hub Bureau for Inclusive Growth, Partnerships, and Innovation. 2023. Available online: https://www.usaid.gov/digital-development (accessed on 18 April 2024).
53. Rajkhowa, P.; Baumüller, H. Assessing the potential of ICT to increase land and labour productivity in agriculture: Global and regional perspectives. *J. Agric. Econ.* **2024**, *75*, 477–503. [CrossRef]
54. Akinlo, T.; Dada, J.T. Information technology, real sector and economic growth in sub-Saharan Africa: A cross-sectional dependence approach. *Qual. Quant.* **2022**, *56*, 4241–4267. [CrossRef]
55. Hogan Warren, P. Technical Progress and the Production Function. *Rev. Econ. Stat.* **1958**, *40*, 407–411. [CrossRef]
56. *Statistics of South Africa. Community Survey, 2016—Agricultural Households*; Report No. 03-01-05; Statistics South Africa: Pretoria, South Africa, 2016.
57. Pesaran, M.H.; Shin, Y. An Autoregressive Distributed lag Modelling Approach to Cointegration Analysis. In *Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium*; Strom, S., Ed.; Cambridge University Press: Cambridge, UK, 1999; Chapter 11; pp. 371–413.
58. Pesaran, M.H.; Shin, Y.; Smith, R. Bounds Testing Approaches to the Analysis of Level Relationships. *J. Appl. Econom.* **2001**, *16*, 289–326. [CrossRef]
59. Regret, S.; Mufandaedza, S.M.; Matsvai, S. Testing the Ricardian Equivalence Hypothesis in Zimbabwe: An ARDL Bound Testing Approach. *J. Econ. Sustain. Dev.* **2015**, *6*, 117–128.
60. Ghouse, G.; Khan, S.A.; Rehman, A.U. *ARDL Model as a Remedy for Spurious Regression: Problems, Performance and Prospect*; Munich Personal RePEc Archive: Munich, Germany, 2018.

61. Birthal, P.S.; Hazrana, J.; Negi, D.S.; Bhan, S.C. Climate change and land-use in Indian agriculture. *Land Use Pol.* **2021**, *109*, 105652. [CrossRef]
62. Devot, A.; Royer, L.; Caron Giauffret, E.; Ayral, V.; Deryng, D.; Arvis, B.; Giraud, L.; Rouillard, J. European Parliament, Directorate-General for Internal Policies of the Union. *The Impact of Extreme Climate Events on Agriculture Production in the EU—Research for AGRI Committee*; Publications Office of the European Union, 2023. Available online: https://op.europa.eu/en/publication-detail/-/publication/bbb9a70a-da6d-11ed-a05c-01aa75ed71a1/language-en (accessed on 17 February 2024).
63. Boyd, R.; Holton, R.J. Technology, Innovation, Employment and Power: Does Robotics and Artificial Intelligence Really Mean Social Transformation? *J. Sociol.* **2018**, *54*, 331–345. [CrossRef]
64. Ali, S.; Jabeen, U.A.; Nikhitha, M. Impact of ICTs on agricultural productivity in Zambia. *Eur. J. Bus. Econ. Account.* **2016**, *4*, 82–92.