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Advancing Somali agriculture through digitalization: assessing the impacts of ICT and foreign direct investment on food production

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Abstract

The integration of information and communication technology (ICT) into Somali agriculture has the potential to transform traditional practices, which enhances efficiency and increases production. Despite ICT's transformative potential, comprehensive empirical studies analysing its combined influence with foreign direct investment (FDI) on food production in Somalia remain scarce. Employing the autoregressive distributed lag (ARDL) technique and Kernel-based regularised least squares (KRLS) methodology, this study examines these relationships using time series data from 1990 to 2022. The findings reveal that agricultural labour, cropped land area, and trade openness significantly enhance food production in the short- and long-run. Remarkably, mobile phone usage exhibits a positive association with food production in Somalia, which reinforces the critical role of digital communication. Conversely, internet usage negatively affects food production, potentially reflecting challenges in integrating technology with traditional practices. Capital and FDI demonstrate adverse but statistically insignificant effects. By reinforcing the ARDL findings further, the KRLS analysis further demonstrates the heterogeneous effects of these variables. Specifically, there is an increasing marginal impact of agricultural labour, land, FDI, trade openness, and mobile usage on food production, while capital and internet usage exhibit decreasing marginal effects. Based on these insights, this study suggests optimising land use, fostering ICT adoption, addressing inefficiencies in capital investments, and enhancing trade openness to support sustainable agricultural growth.

1. Introduction

From primitive tools to advanced information and communication technologies (ICT), agriculture has undergone a profound transformation since the advent of farming. This technological revolution has fundamentally altered food production methodologies and empowered farmers to address both local and global challenges with increased efficacy (Chandio *et al* 2022). Understanding and tackling global agricultural developments is crucial for improving smallholder livelihoods, where ICT plays a vital role (Marechera and Ndwiga 2015). Digital technologies, such as the Internet and mobile phones, facilitate data collection, storage, analysis, and sharing, which revolutionized numerous aspects of daily life (Deichmann *et al* 2016). ICT-enabled agricultural services provide substantial advantages to farmers, including the delivery of useful information and the ability to generate higher profits via improving market accessibility (Kayumova 2017). Access to ICT, particularly mobile phones, has significantly improved agricultural market performance in developing countries, with 70 per cent of the poorest 20 per cent of the population now owning mobile phones (World Bank 2016, Nakasone *et al* 2014). These technologies provide farmers with essential information on market pricing, weather forecasts, and best practices, which enhances productivity and decision-making (Mcfadden *et al* 2022). In addition, a country's central position in the global foreign direct investment (FDI) network is positively associated with its technological advancement (Sultana and Turkina 2020). FDI fosters sustainable agricultural development by supporting digital agriculture and enhancing output through improved land and labour productivity, advanced farming techniques, and better access to inputs and training (Epaphra and Mwakalasya 2017, Nyiwul and Koirala 2022, Chen *et al* 2024).

FDI stimulates economic growth by creating employment opportunities, enhancing technical expertise, and supplying foreign currency, which contributes to increases in GDP, trade, and employment in developing nations (Asiedu 2002, Hung 2003, Abdi *et al* 2024a). It also fosters technological innovation, particularly in agriculture, by introducing advanced practices that enhance efficiency, reduce waste, and improve crop quality (Li 2023, Sultana and Sadekin 2023). However, the impact of FDI on innovation depends on a country's technological development, with positive effects observed only above a certain threshold (Dospinescu 2022). On the other hand, agricultural extension plays a vital role in promoting the growth and long-term viability of farming, especially in the current era of technological advancements. Effective and sustainable agriculture, particularly in small and marginal holdings, hinges on providing farmers with timely, location-specific information and constant communication (MoA 2007). In addition, advances in ICT infrastructure, including mobile phones and internet usage, significantly enhance global agricultural productivity by improving land and labour efficiency, promoting sustainable output, and strengthening food security (Sikdar *et al* 2020, Chandio *et al* 2024, Rajkhowa and Baumüller 2024). Digital technologies bridge information gaps for small-scale farmers, improving agricultural supply chain management, knowledge dissemination, and communication through social media platforms while benefiting the environment, society, and economy (Deichmann *et al* 2016, Zikri *et al* 2024). ICTs provide significant benefits across agriculture, food processing, distribution, and consumption, which enhances efficiency and sustainability in each stage (El Bilali and Allahyari 2018).

The digital economy significantly enhances agricultural productivity, fosters human capital accumulation, and improves governance within the agricultural sector (Wang *et al* 2023). The impact of the digitalization is significant in countries at the higher and lower levels of agricultural development (Wang *et al* 2023). Despite its potential, digital technology faces barriers to adoption, such as limited financial resources, lack of skilled workers, and low digital literacy, particularly in poorer countries where it can only address some agricultural challenges (Deichmann *et al* 2016, Nezamova and Olentsova 2022). Developing countries like Somalia need to digitalize their agricultural sectors for various reasons. Firstly, digitalization has the potential to significantly boost total factor productivity in agriculture, especially in rapidly growing areas where it can mitigate adverse effects on the natural environment (Fu and Zhang 2022). Second, in globalized food systems, digitalization can enhance agricultural supply chain management, which is essential for guaranteeing food safety. This is particularly crucial for developing nations, where information and communication costs significantly affect agricultural output (Panetto *et al* 2020). Finally, the process of digitalization can effectively harness the energy and innovation of the private sector in Somalia, which is crucial for reducing food insecurity and poverty, and achieving economic advancement.

According to Iddrisu *et al* (2015), FDI acts as a crucial source of finance and a possible lifeline for developing countries, especially those grappling with high poverty rates and underdeveloped financial markets. In addition, agriculture serves as the primary source of income for almost 80% of the people in East Africa, emphasizing its significance in creating job opportunities and alleviating poverty (Abdi *et al* 2023). Food availability has significantly increased in the last fifty years due to improved productivity in agriculture (Baldos and Hertel 2014). The global agriculture value-added has shown consistent growth, with an average annual increase of 2.8 per cent. From 2012 to 2021, it rose from USD 2.9 trillion to USD 3.7 trillion (Food and Agriculture Organization 2021). In Somalia, the agriculture sector has experienced significant growth over the years, with the value-added increasing from USD 232 million in 1973 to USD 5,509 million in 2022. This growth has been steady, with an average annual rate of 9.30%. Additionally, it remains challenging to ensure household food security while over a quarter of employment is in agriculture (WDI, 2022). Local entrepreneurs are committed to fostering high-quality innovation and emerging digital technologies (FAO, ITU, 2022). However, Somali farmers face challenges such as inadequate infrastructure, lack of electricity, and extreme weather conditions, including flash floods and droughts (Abdi *et al* 2024b).

Despite the cost of mobile services remaining among the lowest on the continent, driven down by competition among providers and low tariffs, internet penetration in Somalia is relatively low at 12.1 per cent, mobile cellular subscriptions stand at 51 per 100 inhabitants, whereas active mobile broadband subscriptions are much lower, at 2.5 per 100 inhabitants (ITU, 2018). Additionally, Somalia is the African country most reliant on mobile money due to its unique economic environment, with about 55 per cent of the population aged 16 and older utilizing it (World Bank 2018). Moreover, there is a significant shortfall in FDI aimed at enhancing infrastructure, education, institutions, and environmental protection to boost agricultural growth and improve food security (World Bank and FOA 2018). Few studies have explored the influence of ICT and foreign investments on food production in developing countries (Mwalupaso *et al* 2019, Fu and Zhang 2022, Hasan *et al* 2023, Liu and Liu 2023). However, a notable gap persists in East Africa, specifically in Somalia, where a large portion of the population is dependent on the agriculture sector while still facing food insecurity (Abdi *et al* 2024b). The National Development Plan (NDP) for 2020–2024 has identified the telecommunications sector as a strategic priority. Thus, it is necessary to identify to policymakers how strategic investments in telecommunications can directly enhance food production and security. Accordingly, this study aims to investigate the impacts of ICT and FDI on food production in Somalia, utilizing time series data spanning 1990 to 2022.

Given this background, this study contributes to the literature in the following ways. This study represents the first empirical investigation in Somalia to explore the impact of ICT and FDI on food production. The research introduces a novel analytical model that integrates both ICT and FDI, enabling an assessment of how digitalization and international capital inflows contribute to food production in the case of a food-insecure country. In addition to ICT and FDI, the study considers trade openness as a critical factor in understanding food production dynamics because it directly influences agricultural productivity through the availability of advanced technologies, competitive inputs, and larger markets. Besides, this undertaking employs the autoregressive distributed lag (ARDL) method, utilizing the bounds testing approach pioneered by Pesaran *et al* (2001). This technique can accurately delineate both short- and long-run relationships among the variables, even in small sample contexts. Distinct from previous research, this analysis explores the heterogeneous marginal effects on food production using the Kernel-based regularized least squares (KRLS) approach, proposed by Sarkodie and Owusu (2020). The KRLS method, rooted in machine learning, offers a robust framework for interpreting results and effectively addresses heterogeneity, additivity, and nonlinear dynamics within the data. Remarkably, this study finds that agricultural labour and land positively contribute to food production. Trade openness also demonstrates a strong positive impact, which reflects its role in facilitating access to global markets and advanced agricultural inputs. Mobile usage further enhances productivity by improving efficiency and connectivity within the agricultural sector. In contrast, internet usage shows a negative association with food production, which suggests potential challenges in integrating digital technologies with traditional farming practices. Capital and FDI exhibit negative but statistically insignificant effects, which proposes the complex relationships between investments and food production in Somalia.

The structure of the paper is organized as follows: section 2 presents a comprehensive review of the existing literature. Section 3 outlines the data sources and details the econometric methodology employed. Section 4 analyzes the empirical results derived from the study. Finally, section 5 summarizes the essential findings and offers policy recommendations.

2. Literature review

The integration of ICTs into the agricultural sector has consistently been shown to significantly enhance productivity and sustainability across various global regions. For instance, Rengaraj (2022) highlighted the positive impact of television on agricultural productivity, which demonstrates the potential of media technologies to disseminate valuable farming knowledge effectively. Similarly, Hopestone (2014) documented substantial productivity gains in 34 African countries from 2000 to 2011, attributed to broad ICT implementations, which suggests a scalable impact across the continent. Further empirical evidence from Oyelami *et al* (2022) in sub-Saharan Africa (SSA) shows that robust ICT infrastructure can lead to long-term productivity enhancements. However, the effects of ICTs are constrained by operational and regional specifics. Hasan *et al* (2023) reported that while telephone use and labour exhibited positive short-run impacts, internet and mobile phone usage negatively affected land productivity. This indicates that the type of ICT tool and its integration into existing agricultural practices significantly influences outcomes. In addition, Mwalupaso *et al* (2019) demonstrated that mobile phone utilization by Zambian maize farmers led to enhanced technological efficiency and increased food production.

The transformative role of digitalization in agriculture extends beyond enhancing food production to influencing economic well-being and promoting sustainable practices. Kitole *et al* (2024) emphasized that loans, extension services, education, and governmental support are crucial in facilitating agricultural digitalization, which significantly impacts the well-being of smallholder farmers. Similarly, Rolandi *et al* (2021) indicated how digitalization might promote production, improve decision-making, and expand access to markets, ultimately favourably influencing the lives of farmers. Additionally, Liu and Liu (2023) as well as Fu and Zhang (2022) have established that digital technologies boost sustainable agricultural practices and enhance total factor productivity in China. Studies by Mittal and Mehar (2012) and Awuku *et al* (2023) demonstrate the significant impact of mobile technology on agricultural productivity in developing countries. Mobile phones enhance access to crucial information, improving operational efficiency and supporting the growth of small-scale farmers and processors in India and Ghana, respectively. Despite these benefits, challenges remain, particularly in fully leveraging ICT for agricultural supply chains. Van Campenhout (2022) pointed out that while ICTs can enhance market inclusivity and efficiency, their full potential is realized only when accompanied by other strategic measures. Similarly, Abate *et al* (2023) revealed the limited adoption of digital technologies in African agriculture despite their potential to enhance market efficiency. They identified the complexity of agricultural markets and the need for integrated, end-to-end solutions as significant barriers. However, successful cases such as M-Pesa demonstrate the tangible benefits of such innovations.

The diverse research on the effects of FDI on agricultural output provides a different understanding of its impacts across different regions and contexts. Ahmad *et al* (2020) and Awunyo-Vitor and Sackey (2018) have identified a positive correlation between FDI and agricultural productivity. This suggests that foreign investment can bolster agricultural outputs. Gunasekera *et al* (2015) and Brownson Akpan (2021) consistently found that FDI significantly boosts agricultural productivity, which highlights its potential as a catalyst for enhancing agricultural outputs. In addition, FDI can bridge the funding gap required to enhance food security and agricultural productivity, though it may inversely affect food security where land governance is weak (Dogana, 2022). Similarly, Iddrisu *et al* (2015) examined the effects of FDI on Ghana's agricultural performance between 1980 and 2013. Utilizing the Johansen co-integration test, they found that while short-run effects were positive, the long-run impact of FDI was negative. Further investigations into this relationship have employed various econometric models to clarify the nature of the impact. Akinwale *et al* (2018) and Ogbanje and Salami (2022) utilized the vector error correction model (VECM) and reported mixed results, noting both positive and negative influences of FDI on agricultural productivity. This indicates the complexity of the dynamics between foreign investment and sectoral performance.

In contrast, other studies have reported insignificant or adverse outcomes. For example, Sultana and Sadekin (2023) observed a detrimental long-run effect of FDI on agriculture, although an insignificant short-term impact was noted. Similarly, Epaphra and Mwakalasya (2017) reported an insignificant impact of FDI on agricultural productivity. This implies the presence of variability based on local factors or implementation strategies. Focusing on Nigeria, Owutuamor and Arene (2018) applied a range of econometric analyses and discovered only a non-significant positive relationship between FDI and agricultural growth. Edewor *et al* (2018) focused specifically on Nigeria and highlighted a decline in FDI since 2014, which suggests a weakening foreign investment interest in Nigerian agriculture. In addition, Elhaj and Ali (2017) explored the specific impact of FDI on the agricultural productivity of female farmers in Eastern and Southern African nations, covering the period from 1980 to 2013. The study concluded that FDI presence adversely affected women's productivity in agriculture, even when controlling for other variables. Thus, the influence of FDI on food production is context-dependent, influenced by economic policies, governance, and local economic conditions (Ding *et al* 2021). Expanding the lens to include technology, Ofori and Asongu (2021) examined how FDI, coupled with ICT diffusion, promotes inclusive growth in the agrarian SSA, revealing positive synergistic effects. Similarly, Belloumi and Touati (2022) explored the dynamic interactions between FDI inflows, ICT, and economic growth in Arab countries. They found that ICT advancements positively influence FDI inflows over the long-term.

In the European Union, Hart *et al* (2015) found that although trade openness initially reduced agricultural efficiency, it eventually led to improvements, which suggests a delayed beneficial effect. Contrasting this, Hassine and Kandil (2009) observed that trade openness positively influenced the rate of farming productivity and contributed significantly to poverty reduction in developing Mediterranean nations, which indicates the potential for trade policies to support agricultural sectors in less economically developed regions. Meanwhile, Rasheed *et al* (2021) focused on Pakistan and utilized the ARDL approach to discover that while agriculture has a favourable relationship with both trade openness and FDI, it exhibits a negative relationship with gross fixed capital formation. This implies that while trade and foreign investments can be beneficial, excessive capital formation might not always align with agricultural growth. The studies by Inusa and Umaru (2021) and Ju *et al* (2022) offer a different perspective. Despite using different models—Generalized Method Moments (GMM) and ARDL—both studies concluded that trade openness negatively affects the agriculture sector. This suggests that integrating into global markets might have complex repercussions for local agriculture. Additionally, the literature suggests that increased exchange rates is particularly detrimental to agricultural productivity.

The impact of domestic investment on agri-food sectors across different regions has been explored in various studies. Djokoto *et al* (2014) found that in Ghana, FDI in agriculture influences domestic agricultural investment. This suggests that an increase in FDI correlates with an increase in domestic investment, which they describe as having a considerable and favourable association. Conversely, Samuel (2021) examined the impact of domestic investment on Nigeria's crop output from 1981 to 2018 using the ARDL technique. This study found that both human and physical capital investments negatively impacted agricultural output, which suggests substantial discrepancies in investment outcomes within the sector. Agricultural investments not only enhance food output but also contribute to economic growth. Using VECM, Abdelhafidh and Bakari (2019) reveal a positive unidirectional causation from domestic agricultural investment to output growth in Tunisia. Additionally, the literature indicated that labour and land productivity are crucial determinants of food production. For instance, Ali Warsame and Hassan Abdi (2023) discovered bidirectional causation between

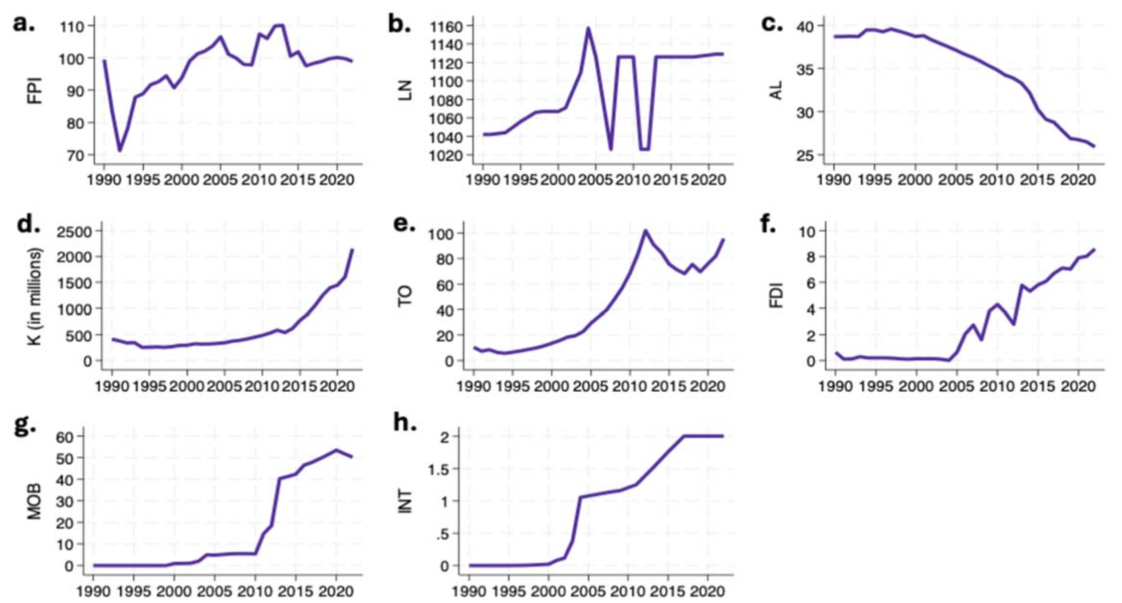

Figure 1. Trends of the sampled variables. (a) food production, (b) agricultural land, (c) agricultural labour, (d) capital, (e) trade openness, (f) foreign direct investment, (g) mobile usage, and (h) internet use.

Table 1. Variables, code, measurement, and sources.

Variable	Symbol	Description	Source
Food production	FP	Food production index (2014–2016 = 100)	WDI
Agricultural labor	AL	Employment in agriculture (% of total employment)	WDI
Agricultural land	LN	Cropland area (1000 ha)	FAO
Capital	K	Gross capital formation, constant 2015 prices	SESRIC
Trade openness	TO	Trade openness index	SESRIC
Foreign direct investment	FDI	Inward FDI (% of GDP)	UNTCAD
Mobile phone usage	MOB	Mobile cellular subscriptions (per 100 people)	WDI
Internet use	INT	Individuals using the Internet (% of population)	WDI

labour and agricultural production through the Granger causality approach. Yurtkuran (2021) notes that agricultural inputs vary significantly by farm type, often originating from within the sector, highlighting the sector's role in sustaining food security and economic stability. However, Rajkhowa and Baumüller (2024) found an insignificant statistical correlation between the use of ICT and land productivity in Africa and Asia.

3. Methodology and data

3.1. Data sources and variables

This study utilizes annual time series data from 1990 to 2022 to investigate factors influencing food production in Somalia. The data were sourced from reliable databases, including the World Bank, the Organization of Islamic Cooperation (OIC) database - SESRIC, the Food and Agriculture Organization (FAO), and the United Nations Conference on Trade and Development (UNCTAD). The dependent variable in this study is food production, while the independent variables include agricultural labour, agricultural land, capital, trade openness, foreign direct investment, mobile phone usage, and internet use. The time frame was selected based on the availability of comprehensive data for all variables. All variables—except for mobile phone usage and internet use—were transformed into their natural logarithms to facilitate a robust statistical analysis. This transformation reduces variance and allows the coefficients to be interpreted as elasticities. Mobile phone usage and internet use were maintained in their original forms to accurately capture the direct impact of technological penetration. Table 1 summarizes the descriptions and sources of the data, while figure 1 illustrates the trends of the independent variables over the study period.

Food production is measured in terms of the food production index, which includes food crops that are considered edible and contain nutrients (Abdi *et al* 2024c). This measure is crucial as it reflects the agricultural sector's ability to meet the population's food demands, particularly in a country like Somalia, where agriculture plays a significant role in the economy. Agricultural labour is quantified by the number of individuals engaged in agricultural activities, land is measured in hectares under cultivation, and capital includes investments in agricultural machinery and infrastructure (Chandio *et al* 2024). Trade openness is calculated as the sum of exports and imports divided by GDP, reflecting the extent of integration into the global economy (Wang *et al* 2023, Abdi *et al* 2024c). Foreign direct investment is measured as inward FDI as a per cent of GDP, representing the proportion of foreign capital relative to the size of the economy. Mobile phone usage and internet use are included as proxies for technological advancement and information accessibility. Mobile phone usage is measured by the number of mobile phone subscriptions per 100 people, and internet use is measured by the percentage of the population using the internet (Chandio *et al* 2024).

3.2. The empirical strategy

3.2.1. The ARDL approach

This study utilizes the ARDL bound test introduced by Pesaran *et al* (2001) to explore the cointegration between the variables. The ARDL procedure delivers distinct advantages over traditional cointegration techniques. Firstly, it accommodates regressors regardless of their integration order—level I(0), first difference I(1), or a combination—provided none are integrated at the second difference I(2). Secondly, it is well-suited for small sample sizes, yielding unbiased and consistent estimates. Thirdly, it concurrently estimates long-run and short-run coefficients, enhancing the clarity of the distinct impacts over time. To investigate the influence of agricultural labour, agricultural land, capital, trade openness, foreign direct investment, mobile phone usage, and internet use on food production in Somalia, we provide the following model—by ensuing the earlier empirical papers by Chandio *et al* (2024) and Hasan *et al* (2023)—as follows:

$$\begin{aligned} \ln FP_t = \alpha_0 + \beta_1 \ln AL_t + \beta_2 \ln LN_t + \beta_3 \ln K_t + \beta_4 \ln TO_t \\ + \beta_5 \ln FDI_t + \beta_6 MOB_t + \beta_7 INT_t + \varepsilon_t \end{aligned} \tag{1}$$

where α_0 is the intercept term, and ln stands for the natural logarithm. lnFP, lnAL, InLN, lnK, lnTO, lnFDI, MOB, and INT represent food production, agricultural labour, agricultural land, capital, trade openness, foreign direct investment, mobile usage, and internet use. Moreover, t and ε denote time and the error term, respectively. The parameters β_1, β_2, β_3, β_4, β_5, β_6 and β_7 are the coefficients of the independent variables. To examine the long- and short-run relationship between food production and its determinants, we estimate the conditional ARDL model corresponding to equation (1), which is formulated as follows:

$$\begin{aligned} \Delta \ln FP_t = \alpha_0 + \phi_1 \ln FP_{t-1} + \phi_2 \ln AL_{t-1} + \phi_3 \ln LN_{t-1} + \phi_4 \ln K_{t-1} \\ + \phi_5 \ln TO_{t-1} + \phi_6 \ln FDI_{t-1} + \phi_7 MOB_{t-1} \\ + \phi_8 INT_{t-1} + \sum_{i=1}^{p} \lambda_1 \Delta \ln FP_{t-i} + \sum_{i=1}^{q} \lambda_2 \Delta \ln AL_{t-i} \\ + \sum_{i=1}^{q} \lambda_3 \Delta \ln LN_{t-i} + \sum_{i=1}^{q} \lambda_4 \Delta \ln K_{t-i} + \sum_{i=1}^{q} \lambda_5 \Delta \ln TO_{t-i} \\ + \sum_{i=1}^{q} \lambda_6 \Delta FDI_{t-i} + \sum_{i=1}^{q} \lambda_7 \Delta MOB_{t-i} + \sum_{i=1}^{q} \lambda_8 \Delta INT_{t-i} + \varepsilon_t \end{aligned} \tag{2}$$

where ϕ_1–ϕ_8 stand for the long-run coefficient parameters, λ_1–λ_8 are the short-run coefficients of the variables, p and q indicates the optimal lag length of the dependent and explanatory variables, and Δ is the first difference sign that indicates short-run parameters. To test the presence of long-run cointegration among the variables, we first determine the optimal lag length using a general-to-specific approach. Subsequently, we employ the F-bounds test to assess the null hypothesis (H_0: $\phi_1 = \phi_2 = \phi_3 = \phi_4 = \phi_5 = \phi_6 = \phi_7 = \phi_8 = 0$) that the series are not cointegrated. This is tested against the alternative hypothesis (H_a: $\phi_1 \neq \phi_2 \neq \phi_3 \neq \phi_4 \neq \phi_5 \neq \phi_6 \neq \phi_7 \neq \phi_8 = 0$) that the series are cointegrated in the long-run. The bounds test thus helps in discovering both the short- and long-run relationships between food production and its determinants. Building on the cointegration analysis described in equation (2), we examine the short-run dynamics between the predictors and dependent variables through error correction models (ECM). In this model, the symbol ψ represents the coefficient of the error correction term (ECT). Consequently, equation (3) can be reinterpreted within the error correction framework as follows:

$$
\begin{aligned}
\Delta \ln FP_t = \alpha_0 &+ \sum_{i=1}^{p} \lambda_1 \Delta \ln FP_{t-i} + \sum_{i=1}^{q} \lambda_2 \Delta \ln AL_{t-i} \\
&+ \sum_{i=1}^{q} \lambda_3 \Delta \ln LN_{t-i} + \sum_{i=1}^{q} \lambda_4 \Delta \ln K_{t-i} \\
&+ \sum_{i=1}^{q} \lambda_5 \Delta \ln TO_{t-i} + \sum_{i=1}^{q} \lambda_6 \Delta FDI_{t-i} + \sum_{i=1}^{q} \lambda_7 \Delta MOB_{t-i} \\
&+ \sum_{i=1}^{q} \lambda_8 \Delta INT_{t-i} + \psi ECT_{t-1} + \varepsilon_t
\end{aligned} \tag{3}
$$

3.2.2. Kernel-based regularized least squares (KRLS)

To enhance the robustness of the ARDL results, this study utilizes the KRLS approach, a machine-learning algorithm that incorporates pointwise derivatives. By handling nonlinearity and heterogeneity within the data, it has the ability to correct spurious regression problems inherent in linear models (Hainmueller and Hazlett 2014). By allowing for smooth adjustments of marginal effects, KRLS effectively addresses the limitations of linear models, which often only account for average effects (Brambor *et al* 2006). The KRLS estimator is superior to standard ARDL models, which do not account for time variations and nonlinearity, as it allows for the evaluation of dynamic interactions and nonlinear effects (Sarkodie and Owusu 2020). To assess the heterogeneous (nonlinear) impacts of ICT and FDI on food production in Somalia, the KRLS estimator provides consistent inferences that provide insights crucial for policies enhancing food production. The KRLS model can be expressed as follows:

$$\hat{f}(\mathrm{x}) = \sum_{i=1}^{N} \alpha_i K(x^*, \mathrm{x}_i) \tag{4}$$

where $\hat{f}(\mathrm{x})$ is the estimated function, α_i are the coefficients estimated by the model, $K(x^*, \mathrm{x}_i)$ is the kernel function. Typically, the Gaussian radial basis function (RBF) kernel can be written as follows:

$$K(x_j, x_i) = \exp\left(-\frac{\|x_j - x_i\|^2}{\sigma^2}\right) \tag{5}$$

σ^2 is the hyperparameter that controls the width of the kernel. The pointwise derivative, or marginal effect, of the KRLS model can be calculated as:

$$\frac{\partial \hat{f}(\mathrm{x})}{\partial x_j} = \sum_{i=1}^{N} \alpha_i \frac{\partial K(\mathrm{x}, \mathrm{x}_i)}{\partial x_j} \tag{6}$$

where x_j is the *j*th explanatory variable. Consequently, the model's quality is evaluated using diagnostic techniques suggested by Brown *et al* (1975), including the CUSUM tests, which verify the stability of the model. Additionally, serial correlation is confirmed using the Durbin's test, while heteroscedasticity is assessed with the Breusch-Pagan-Godfrey test. The skewness and kurtosis tests are conducted to diagnose residual normality.

4. Empirical results and discussion

4.1. Descriptive statistics

The empirical results derived from the summary statistics and correlation matrix, as shown in Panel A of table 2, provide several key insights. Firstly, mobile usage exhibits the highest mean value of 16.665, followed by capital, which has a mean value of 8.689. Each variable's values fall within their respective minimum and maximum ranges, which indicates convergence and a low likelihood of outliers. Mobile usage presents the largest variability, with a standard deviation of 21.193. This is followed by FDI with a standard deviation of 0.822, internet use (0.810), and trade openness (0.438). Conversely, the variable with the least variability is the cropped land area, with a standard deviation of 0.016, followed by food production, which has a standard deviation of 0.040. In terms of skewness, all variables exhibit negative skewness, except for capital, mobile usage, and internet use, which have positive skewness. Regarding kurtosis, most of the variables are platykurtic, indicating a flatter distribution than normal, except for food production, which is leptokurtic, suggesting a more peaked distribution. Based on the Jarque-Bera statistics, it can be concluded that all variables follow a normal distribution, except for food production. On the other hand, the correlation analysis reveals mixed relationships between the variables and food production. While trade openness (0.705) and internet use (0.566) show strong positive correlations with food production, cropped land area (−0.364) exhibits a negative correlation. These results suggest varying impacts of the variables on the dependent variable.

Table 2. Summary statistics.

Panel A: summary statistics								
	lnFP	lnAL	lnLN	lnK	lnTO	lnFDI	MOB	INT
Mean	1.987	1.540	3.037	8.689	1.456	−0.051	16.665	0.906
Maximum	2.042	1.597	3.063	9.333	2.009	0.934	53.480	2.004
Minimum	1.853	1.414	3.011	8.403	0.750	−2.000	0.000	0.000
Std. Dev.	0.040	0.061	0.016	0.265	0.438	0.822	21.193	0.810
Skewness	−1.499	−0.898	−0.199	0.964	−0.242	−0.342	0.801	0.061
Kurtosis	5.628	2.333	1.543	2.754	1.462	1.896	1.802	1.409
Jarque−Bera	21.860	5.046	3.138	5.199	3.576	2.319	5.503	3.500
Probability	0.000	0.080	0.208	0.074	0.167	0.314	0.064	0.174
Observations	33	33	33	33	33	33	33	33
Panel B: correlation matrix								
lnFP	1.000							
lnAL	−0.364	1.000						
lnLN	0.444	−0.599	1.000					
lnK	0.321	−0.986	0.537	1.000				
lnTO	0.705	−0.806	0.575	0.776	1.000			
lnFDI	0.450	−0.815	0.372	0.799	0.846	1.000		
MOB	0.354	−0.965	0.599	0.934	0.773	0.785	1.000	
INT	0.566	−0.917	0.660	0.879	0.937	0.850	0.888	1.000

Table 3. Unit root analysis.

Variable	Level		First difference	
	ADF	PP	ΔADF	ΔPP
lnFP	−1.847	−2.030	-5.144^{***}	-5.454^{***}
lnAL	3.476	2.501	-2.687^{*}	-2.518^{*}
lnLN	−2.789	−2.556	-5.581^{***}	-6.422^{***}
lnK	3.210	2.661	-3.315^{**}	-3.267^{**}
lnTO	−0.128	−0.368	-4.756^{***}	-4.750^{***}
lnFDI	−1.214	−0.964	-6.826^{***}	-7.402^{***}
MOB	0.338	0.057	-4.633^{***}	-4.740^{***}
INT	−0.096	−0.263	-3.834^{***}	-3.797^{***}

4.2. Unit root tests

To address the non-stationarity issues frequently encountered in time-series data, which can lead to spurious estimations, we conducted several unit root tests. These tests included the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. The null hypothesis (H0) for both tests posits that the series has a unit root (i.e., it is non-stationary), while the alternative hypothesis (Ha) suggests that the series is stationary. As presented in table 3, the ADF and PP test statistics indicate the presence of a unit root or non-stationarity for all variables such as food production, agricultural labour, cropped land area, trade openness, FDI, mobile usage, and internet use at their levels. However, when the variables are first-differenced, the t-statistics from both tests suggest that the series becomes stationary. Given these findings, evaluating the ARDL model is appropriate, as it handles variables regardless of their integration order, except for higher-order, i.e., I(2). This approach ensures robust and reliable estimation of the long-run and short-run relationships among the variables.

4.3. Lag selection criteria and the ARDL estimation approach

The ARDL model requires the selection of appropriate lags for both the dependent and independent variables. Various validation criteria, including the Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Hannan-Quinn Information Criterion (HQIC), are extensively utilized for this purpose. The results of these lag selection criteria are presented in table 4. Among these, the AIC is particularly valuable for establishing the lag sequence, as it identifies the best lag order with the lowest value. In this analysis, the AIC, along with HQIC and SBIC, identifies lag 4 as the optimal lag order, with AIC achieving its lowest value at −459.381. Additionally, the highest LR statistic (8401.700) further supports the choice of lag 4. Moreover, the bounds test is conducted by comparing the asymptotic upper and lower critical values, as provided by Pesaran

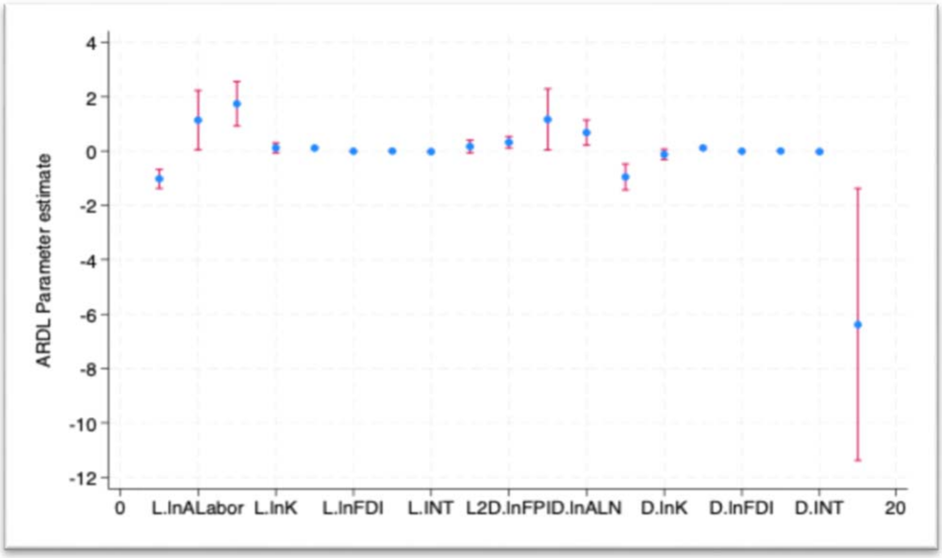

Figure 2. Parameter estimates of the ARDL model. Notes: The blue (●) symbols indicate the estimates in a log–log model, while the olive teal long-dash line with 2 dots represents the reference line. The red spikes mark the lower and upper 95% confidence limits.

Table 4. Lag length criteria.

Lag	LogL	LR	FPE	AIC	HQIC	SBIC
0	195.401	.	0.000	−12.924	−12.806	−12.547
1	445.290	499.780	0.000	−25.744	−24.681	−22.350
2	569.414	248.250	0.000	−29.891	−27.882	−23.479
3	2692.200	4245.600	0.000*	−171.876	−168.923	−162.446
4	6893.030	8401.700*	.	−459.381*	−455.956*	−448.443*

Table 5. Bounds testing using the Pesaran, Shin, and Smith approach.

		10%		5%		1%		p-value	
Statistic	K	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
F	7.420	2.409	3.903	2.967	4.714	4.413	6.794	0.001	0.006
T	−6.190	−2.455	−4.059	−2.862	−4.583	−3.719	−5.695	0.000	0.005

et al (2001), with the calculated F-statistic. The results, presented in table 5, show that the joint F-statistic of the explanatory variables is 7.420, which exceeds the upper critical values (I(1)) at all significance levels (10%, 5%, and 1%). Similarly, the absolute value of the t-statistic (−6.190) surpasses the upper critical value at all significance levels. Therefore, the null hypothesis (H_0) is rejected, confirming the presence of co-integration among the variables. Based on this finding, the long-run model, represented by the ECM, is estimated. Moreover, figure 2 provides the parameter estimates of the ARDL model.

Table 6 presents the estimation of the ARDL model with lagged variables, illustrating both long-run and short-run effects. In the long-run and short-run, agricultural labour has a positive impact on food production in Somalia, which is statistically significant. Specifically, a 1% rise in agricultural labour results in a 1.140% boost in food production in the long-run and a 1.168% increase in the short-run. This implies that enhancing the agricultural labour force can significantly boost food production, thereby supporting economic growth and food security in Somalia. In addition, immediate investments in agricultural labour can yield quick gains in food production. This is aligned with the findings of Pawlak and Kołodziejczak (2020) and Putra (2022), who also concluded that agricultural labour positively influences food production. Furthermore, the findings indicate that agricultural land positively affects food production in Somalia. In the long-run, a 1% increase in agricultural land results in a 1.742% increase in food production and a 0.680% increase in the short-run. This aligns with Marechera and Ndwiga (2015), who demonstrated the crucial role of cropped land area in food production. This suggests that expanding agricultural land can significantly increase food production, which supports long-term

Table 6. Estimation of the ARDL model.

Equation	Variable	Coefficient	Std. err.	Min 95	Max 95
ECT					
	$\ln FP_{t-1}$	-1.025^{***}	0.166	−1.376	−0.674
Long-run					
	$\ln AL_{t-1}$	1.140^{**}	0.514	0.050	2.230
	$\ln LN_{t-1}$	1.742^{***}	0.385	0.925	2.558
	$\ln K_{t-1}$	0.117	0.086	−0.065	0.299
	$\ln TO_{t-1}$	0.111^{***}	0.014	0.081	0.142
	$\ln FDI_{t-1}$	−0.006	0.005	−0.017	0.006
	MOB_{t-1}	0.001^{**}	0.000	0.000	0.002
	INT_{t-1}	-0.024^{*}	0.012	−0.049	0.002
Short-run					
	$\Delta\ln AL_t$	1.168^{**}	0.530	0.044	2.292
	$\Delta\ln LN_t$	0.680^{***}	0.220	0.213	1.146
	$\Delta\ln LN_{t-1}$	-0.955^{***}	0.225	−1.431	−0.479
	$\Delta\ln K_t$	−0.124	0.089	−0.312	0.064
	$\Delta\ln TO_t$	0.114^{***}	0.024	0.064	0.165
	$\Delta\ln FDI_t$	−0.006	0.006	−0.018	0.006
	ΔMOB_t	0.001^{**}	0.001	0.000	0.002
	ΔINT_t	-0.024^{*}	0.012	−0.050	0.001
	Constant	-6.379^{**}	2.360	−11.383	−1.375
ARDL (3,0,2,1,0,0,0,0)					
	Obs.	30	Root MSE	0.009	
	R^2	0.871	Adj. R^2	0.767	

food security and economic stability in Somalia. However, in the short-run, changes in agricultural land lead to decreased food production in Somalia. This finding is consistent with Mireille *et al* (2019) and Piploda and Dwivedi (2024), who found that land use changes can negatively affect natural resources like water and soil, which leads to agricultural land degradation and ultimately reduces food production. This proposes the need for implementing sustainable land management practices to prevent short-term negative impacts on food production.

Capital exhibits a statistically insignificant relationship with food production in Somalia in the long-run and short-run. Specifically, a 1% increase in capital is associated with a 0.117% increase in food production in the long-run and a 0.124% decrease in the short-run, but neither effect is statistically significant. This suggests that while capital might theoretically influence food production, its practical impact is constrained. These constraints could stem from financial challenges and debt burdens that hinder farmers' or agricultural enterprises' ability to invest in essential inputs, modern technology, or infrastructure. Ding *et al* (2021) highlighted that smallholder farmers often struggle to access technological innovations due to financial limitations. In Somalia, this indicates that simply increasing capital without addressing systemic financial and structural barriers is unlikely to enhance food production outcomes meaningfully. By the same token, the results indicate that FDI has a statistically insignificant and negative impact on food production in both the long- and short-run. Specifically, a 1% increase in FDI is associated with a 0.006% decrease in food production in the long-run and a 0.006% decrease in the short-run. These findings are inconsistent with the conclusions of Yao *et al* (2020), Djokoto *et al* (2022), and Nyiwul and Koirala (2022), who reported a positive relationship between FDI and food production. The discrepancy could be attributed to contextual factors unique to Somalia, such as insufficient infrastructure, political instability, or ineffective utilization of foreign investments in the agricultural sector, which may undermine the potential benefits of FDI on food production.

Moreover, trade openness promotes food production in both the long- and short-run. Specifically, a one per cent increase in trade openness results in a 0.111% increase in food production in the long-run and a 0.114% increase in the short-run. The positive impact of trade openness on food production aligns with the findings of Schneider and Kernohan (2006), Ogundari and Awokuse (2016), and Wang *et al* (2023). This implies that increasing trade openness can significantly boost food production in Somalia. This necessitates the formulation of strategies to enhance trade openness, such as reducing trade barriers, improving trade infrastructure, and fostering international trade partnerships. This can facilitate access to international markets, the inflow of agricultural inputs, and advanced technologies that contribute to increased food production in Somalia.

The results reveal remarkable insights into the impact of mobile and internet usage on food production in Somalia. Mobile usage has a positive and statistically significant impact on food production in both the long and short run. Specifically, a 1% increase in mobile usage is associated with approximately a 0.001% increase in food

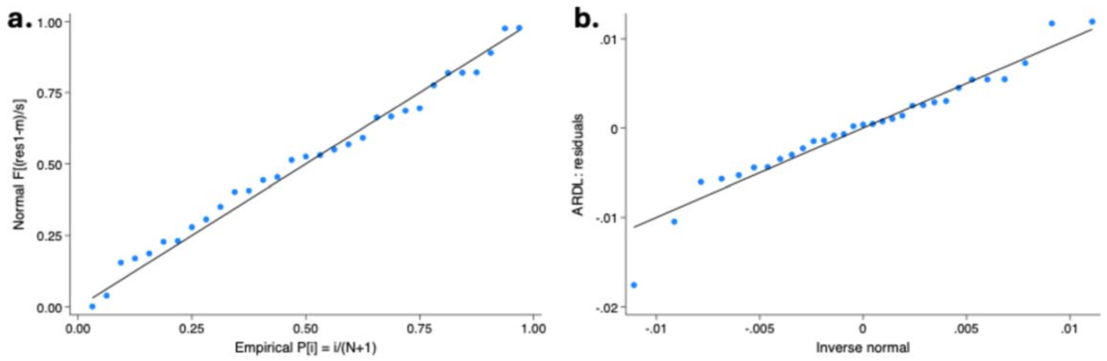

Figure 3. Normal distribution of the estimated residuals. (a) Standardized normal probability plot. (b) Quantiles of residuals against quantiles of normal distribution.

Table 7. Diagnostic tests.

Test		F/χ^2	prob$>\chi^2$
Durbin's test for autocorrelation		3.667	0.0845
Heteroskedasticity		30.00	0.4140
Skewness		16.84	0.5343
Kurtosis		0.010	0.9386
Skewness and kurtosis tests for normality			
Pr(skewness)	0.6664		
Pr(kurtosis)	0.8911	0.200	0.9028

production. This aligns with the outcomes of Szilagyi and Herdon (2006) and Mwalupaso *et al* (2019), who revealed that mobile phone use enhances cost efficiency and overall productivity in food production. Mobile usage allows Somali farmers to access critical information on markets, financial services, and weather forecasts, thereby boosting efficiency and productivity. Conversely, internet usage shows a negative relationship with food production in both the long and short run. A 1% increase in internet usage correlates with a 0.024% decrease in food production. These results contradict the findings of Onyeneke *et al* (2023), who reported that internet usage significantly improved crop production and empowered African consumers. Similarly, Bi *et al* (2022) and Zheng *et al* (2022) found that internet usage increased maize yields and boosted grain output by enhancing technology adoption. These results suggest that in the Somali context, barriers such as inadequate infrastructure, digital literacy, and accessibility might hinder the effective utilization of internet resources in the agricultural sector.

As part of the diagnostic tests outlined in table 7, several evaluations were conducted to validate the assumptions of the dynamic ARDL model, including tests for autocorrelation, heteroscedasticity, and normality. The Durbin test for autocorrelation yielded a p-value exceeding the 0.05 significance threshold, which indicates that the H_0 of no autocorrelation cannot be rejected. Therefore, the residuals are not autocorrelated. Regarding heteroscedasticity, the test results showed a p-value above the 0.05 significance level, meaning the H_0 of homoscedasticity cannot be rejected, and the residuals are homoscedastic. Additionally, the normality of the residuals was assessed using the skewness and kurtosis tests. The findings indicated that the H_0 of normal distribution cannot be rejected at the 0.05 significance level, which confirms that the residuals are normally distributed around the mean. These diagnostic test results affirm the reliability and validity of the ARDL model used in this study.

The validity of the normality assumption, initially verified by the skewness/kurtosis test, was further checked using a standardized normal probability plot (figure 3(a)) and a quantile-quantile (Q-Q) plot comparing the quantiles of residuals against the quantiles of a normal distribution (figure 3(b)). Both graphs confirm that the residuals, calculated using the ARDL (3,0,2,1,0,0,0,0) model, follow a normal distribution. Additionally, the stability of the predicted parameters was assessed using the cumulative sum (CUSUM) test. As shown in figure 4, the results indicate that the calculated parameters' test statistic remains within the 95% confidence range. Thus, the stability of the calculated coefficients over time is confirmed, supporting the robustness of the model's estimates.

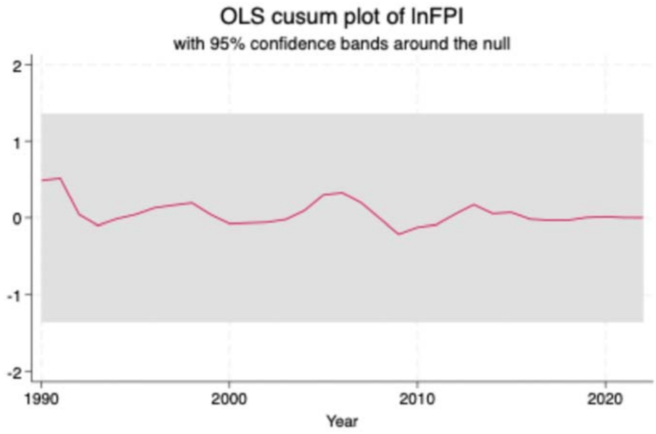

Figure 4. OLS cumulative sum (CUSUM) chart for assessing parameter stability.

Table 8. Individual point derivatives using KRLS.

lnFP	Avg.	SE	t-statistic	p-value	P-25	P-50	P-75
lnAL	0.057	0.026	2.201	0.037	0.042	0.057	0.081
lnLN	0.784	0.175	4.473	0.000	−0.252	0.322	1.920
lnK	−0.016	0.014	−1.096	0.283	−0.026	−0.013	−0.003
lnTO	0.032	0.007	4.408	0.000	0.010	0.022	0.054
lnFDI	0.009	0.004	2.091	0.046	0.000	0.004	0.019
MOB	0.000	0.000	1.423	0.167	0.000	0.000	0.000
INT	−0.002	0.003	−0.732	0.471	−0.007	−0.003	0.002
Diagnostics							
Lambda	0.3303						
Tolerance	0.033						
Sigma	7						
Eff. df	8.341						
R^2	0.7472						
Looloss	0.5729						
Obs	33						

4.4. Kernel-based regularized least squares (KRLS)

An inherent limitation of the ARDL bound test is its assumption of constant marginal effects of variables over time. To account for the varied impacts of the factors collected, we employed the KRLS machine learning method proposed by Hainmueller and Hazlett (2014). The results of the KRLS analysis are presented in table 8. It highlights the heterogeneous marginal effects of the sampled variables at the 25th, 50th, and 75th percentiles. The findings indicate that agricultural labour, cropped land area, trade openness, and FDI significantly contribute to food production, which reinforces the results obtained from the ARDL model. However, while mobile usage positively impacts food production in Somalia, capital and internet usage appear to hinder it, although these effects are statistically insignificant. Various diagnostic tests, including lambda, looloss, and tolerance, were conducted as detailed in table 8. The mean pointwise marginal impact of agricultural labour suggests that an average increase in agricultural labour improves food production by 0.057%. At the 25th percentile, agricultural labour enhances food production by 0.042%, whereas at the 50th and 75th percentiles, it increases food production by approximately 0.057% and 0.081%, respectively. Similarly, agricultural land exhibits variable marginal impacts on food production. On average, an increase in cropped land area improves food production by roughly 0.784%. At the 25th percentile, agricultural land negatively influences food production, but at the 50th and 75th percentiles, it positively influences food production by approximately 0.322% and 1.920%, respectively.

The mean pointwise marginal impact of trade openness is 0.032%. This indicates that an average increase in trade openness positively influences food production by approximately 0.032%. At the 25th percentile, trade openness favourably contributes to food production by 0.01%, while at the 50th and 75th percentiles, it increases food production by 0.022% and 0.054%, respectively. Similarly, FDI has variable marginal impacts on food production. On average, an increase in FDI improves food production by about 0.009%. At the 25th

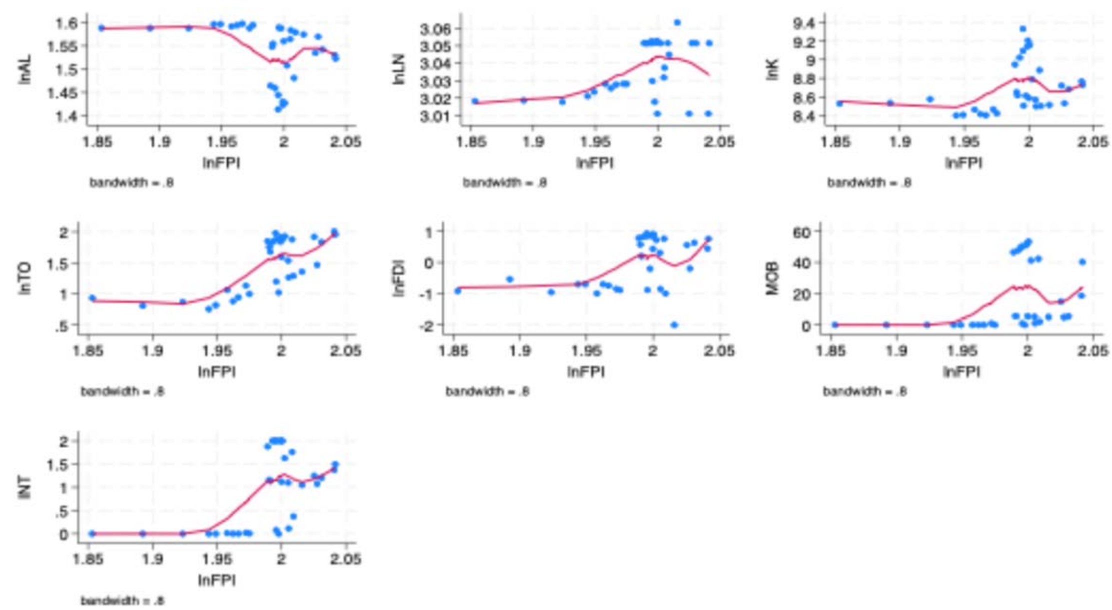

Figure 5. Depiction of the pointwise marginal impact of the explanatory variables on food production.

percentile, foreign investments have a slight positive influence on food production, but at the 50th and 75th percentiles, FDI promotes food production by roughly 0.022% and 0.054%, respectively. The mean pointwise marginal effect of mobile usage is 0.00%. This stages that an average increase in mobile usage has a statistically insignificant impact on food production across various percentiles. Conversely, average increases in capital and internet usage cause food production to fall by around 0.016% and 0.002%, respectively, which are also statistically insignificant. However, in the highest percentile, capital negatively influences food production, while internet usage exhibits a positive and growing marginal impact on food production. These findings highlight the importance of considering the heterogeneous effects of agricultural labour, land, capital, trade openness, FDI, mobile usage, and internet usage on food production in Somalia. Moreover, the model demonstrates a predictive value of 0.74, which indicates that the explanatory variables together account for 74% of the variability in food production in Somalia.

Figure 5 illustrates the pointwise marginal impacts of various factors on food production in Somalia, using the KRLS method to capture both long-run and short-run effects. The pointwise marginal impact of agricultural labour on food output initially remains stable with minimal variation but decreases as food production increases, which indicates diminishing returns to agricultural labour. This suggests that while agricultural labour contributes to food production, its impact becomes less pronounced at higher levels of food output. Additionally, the marginal effect of agricultural land on food production proposes a positive impact in the long-run, with increasing agricultural land leading to higher food output. However, this positive impact diminishes in the short-run, which indicates that additional increases in agricultural land might have diminishing returns or even a negative effect on food production in the short-run. In contrast, the marginal effect of capital on food output indicates a consistently negative impact in both the long- and short-run. An increase in capital initially results in a negative effect on food production, which suggests that higher levels of capital, without proper allocation or management, may hinder food output.

Trade openness exhibits a consistently positive marginal impact on food production in Somalia, both in the long- and short-run. An increase in trade openness enhances food output, which demonstrates the crucial role of open trade policies in facilitating access to agricultural inputs, markets, and technologies that boost food production. Similarly, the marginal effect of FDI on food output remains positive, which reinforces the importance of foreign investments in strengthening the agricultural sector. This demonstrates how FDI contributes to improved infrastructure, technology transfer, and productivity, thereby enhancing food production capabilities. Mobile usage also shows a positive and sustained marginal impact on food production in both the short- and long-run. The increased use of mobile technology fosters better communication, access to market information, and agricultural innovations, which collectively boost productivity and efficiency in the agricultural sector. In contrast, internet usage displays a mixed marginal effect on food production. While it initially has a positive impact, likely due to improved access to knowledge and digital tools, this effect diminishes over time. Excessive reliance on internet usage without corresponding advancements in infrastructure or digital literacy may lead to inefficiencies, reducing its long-term effectiveness in supporting agricultural productivity.

5. Conclusion and policy insights

This study investigated the impact of ICT and foreign direct investment on food production in Somalia during 1990 and 2022. Employing advanced analytical techniques such as ARDL bounds testing and the KRLS method, this study comprehensively analyses the long- and short-run relationships between key variables, accounting for heterogeneity, additivity, and nonlinear dynamics within the data. The empirical results from the ARDL technique indicate that agricultural labour and land positively impact food production in both the long- and short-run. This conveys that increasing the agricultural labour force and optimizing land use can enhance food output sustainably. However, capital and FDI negatively affect food production in the long- and short-run, although statistically insignificant. Additionally, trade openness exhibits positive impacts on food production across both time frames. This reflects the benefits of economic integration in boosting agricultural output. Mobile usage contributes positively to food production in the long-run and the short-run. This signifies that mobile technology can enhance agricultural efficiency and productivity over time. Conversely, internet usage negatively impacts food production in the long-run and the short-run. This indicates that while initial internet access leads to improved productivity as users adapt and integrate new technologies, it eventually may disrupt traditional agricultural practices. The KRLS analysis highlights the diverse marginal effects of the regressors on food production, which reinforces the findings from the ARDL model. Agricultural labour and land exhibit heterogeneous increasing marginal effects, significantly contributing to higher food output. In contrast, capital and internet usage demonstrate heterogeneous decreasing marginal effects, although these effects are statistically insignificant. Mobile usage shows heterogeneous increasing marginal effects on food production in Somalia.

In light of these findings, the study proposes the following policy suggestions. Firstly, to enhance food production, policymakers should focus on increasing the agricultural labour force and optimizing land use. The positive impact of agricultural labour and land on food output in both the long- and short-run stresses the importance of investments in agricultural training programs, extension services, and land management practices. These measures can help sustainably boost food output and improve overall agricultural productivity. Secondly, it is necessary to handle the inefficiencies or misallocations in capital investments within the agricultural sector. Since capital negatively impacts food production, policies should aim to improve the allocation and utilization of capital. This could involve delivering better financial support and guidance to farmers and promoting effective agricultural technologies. Thirdly, policymakers should create a favourable environment for FDI and trade by implementing policies that reduce barriers to investment, improve regulatory frameworks, and enhance trade infrastructure. This approach can attract more foreign investments and open new markets for agricultural products. Fourthly, promoting mobile technology in agriculture is essential, given its positive contribution to food production in the long- and short-run. Policies should encourage the widespread adoption of mobile technologies by supporting initiatives that provide farmers with access to mobile phones, relevant agricultural apps, and mobile-based information services. Finally, internet usage negatively impacts food production in both the short- and long-run. Policymakers should focus on minimizing these adverse effects by ensuring that the introduction of internet technologies does not disrupt traditional agricultural practices. Efforts should include providing farmers with comprehensive training to effectively integrate digital tools into farming operations while safeguarding traditional methods.

While this study provides valuable insights into the impacts of ICT and FDI on food production in Somalia, it is not without limitations. First, the analysis relies on aggregate data for mobile phone and internet usage, which may overestimate their direct effects on the agricultural sector due to the lack of sector-specific ICT adoption data. Second, the relatively small sample size limits the generalizability of the findings beyond the Somali context. Finally, while the ARDL and KRLS approaches offer robust analytical tools, future research could explore alternative methods or panel data to account for regional variations and temporal dynamics. Addressing these limitations presents opportunities for further studies to deepen our understanding of ICT and FDI in agriculture across diverse contexts.

Declarations

Ethical approval

This study follows all ethical practices during writing. We declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere.

Consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The author declares no competing interests.

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Data availability statement

The data used in this study were obtained from publicly available databases, as detailed in the manuscript. While the data are accessible to the public, they were sourced from multiple platforms, each with specific access procedures or registration requirements.The datasets used and/or analyzed during the current study are available from the author on reasonable request. The data that support the findings of this study are available upon reasonable request from the authors.

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