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# Assessing the determinants of agricultural productivity in Somalia: An application of an ARDL model

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## ABSTRACT

This study delves into the factors that boost agricultural productivity while taking five macroeconomic variables into account. The investigated variables are agricultural productivity, which is used as the dependent variable, while employment in agriculture, gross capital formation, arable land, and rainfall are the independent variables. Employing an autoregressive distributed lags (ARDL) model, this paper examines the determinants of agricultural productivity in Somalia from 1991 to 2020. The cointegration between the model's variables was verified using a bounds-testing approach to cointegration. Employment in agriculture was found to have both a short-run and long-run positive impact on agricultural productivity. Similarly, it was discovered that both gross capital formation and the availability of arable land had a favorable influence on agricultural productivity in the short and long run. Additionally, the study indicated a positive short-run and long-run correlation between rainfall and agricultural productivity, although this correlation is statistically insignificant at a five percent level. In the long run, the amount of available arable land has a positive impact on agricultural productivity. However, in the short run, this determinant has the opposite effect. Based on the results, the study advises the government, policymakers, and other concerned authorities to prioritize technological innovation and climate-smart agricultural systems to boost sector productivity.

**Contribution/Originality:** This paper provides new insights into the determinants of agricultural productivity in Somalia. Since Somalia is heavily dependent on the agricultural sector, the government should target agricultural diversification at the community/household levels. Thus, this paper provides insights to policymakers/practitioners who seek to make informed decisions about the determinants of agriculture.

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## 1. INTRODUCTION

Agriculture is critical to attaining sustainable development and the eradication of hunger and poverty. Agriculture is one of the most effective strategies for alleviating extreme poverty, fostering and sharing prosperity, and feeding the world's population, which is estimated to reach 9.7 billion people by 2050 (World Bank, 2022). For many countries across the African continent, agriculture is still one of the most significant economic sectors and a major source of employment and livelihood. The agriculture sector accounts for around 14% of the total gross domestic product (GDP) of the nations in the Sub-Saharan African (SSA) region, and it employs the vast majority of the continent's working population (OBG, 2021). The agricultural industry in Africa has shown promising signs of development in recent years, with agricultural production growing by 13% per year between 2015 and 2020 (AfDB, 2021). Despite this progress, however, the agricultural sector continues to be characterized by low technology, rainfed farming, and small-scale farmers with limited irrigation systems (Jellason, Robinson, & Ogbaga, 2021). On top of that, the agricultural sector faces institutional challenges and negligence (Goyal & Nash, 2017). Recurrent droughts, floods, and cyclones have reduced agricultural production systems in recent years, and many African countries are dealing with transboundary animal diseases and pest invasions, such as the peste des petits ruminants virus, desert locust invasions, and swarms, a situation exacerbated by COVID-19 disruptions (AfDB, 2021).

The agricultural industry provides significant employment opportunities across the African countries. According to Statista (2022), the number of people engaged in Africa's primary industry increased from roughly 197 million in 2011 to 226 million in 2021. Therefore, the agricultural industry remains a pillar of Africa's economy, employing approximately 44 percent of the working population in Africa in 2020, strongly contributing to the continent's job market (Statista, 2022). In 2021, the agriculture sector represented 17 percent of the total GDP of SSA countries, a slight growth of only 2 percent compared to 2011 (Galal, 2023). Agriculture is the primary source of income for more than half of the people in SSA nations, making it a crucial sector for the expansion of the economy. Even though agriculture is widely recognized as vital to the economy of rural areas, a recent survey indicated that 10–25% of urban households rely on it as their primary source of income as well (OECD & FAO, 2016).

Agriculture continues to play a crucial role in Somalia's quest to lift itself out of abject poverty and propel its economy forward. The crop and livestock subsectors have been impacted by several factors, including an environment that is more fragile and degraded than ever before, increased frequency and severity of drought and flooding cycles as a result of worsening climate change, and a lack of research and agricultural extension services. Moreover, crop production is severely and continuously affected by insecurity in the most arable land of Somalia, caused by weak government institutions, recurrent floods, and infrastructure problems (World Bank & FAO, 2018a). Despite the difficulties encountered by the crop and livestock subsectors over the past three decades, the agricultural sector continues to be the primary driver of Somalia's economic activity, exports, and employment (World Bank & FAO, 2018b). As a result, the long-term development and economic revival of Somalia depend heavily on these subsectors.

The agricultural sector is a major contributor to Somalia's GDP. The livestock and crop subsectors continue to be the main drivers and backbone of economic activities, exports, and employment in Somalia. The agriculture sector is responsible for more than 75 percent of Somalia's GDP and 93 percent of the country's total exports (World Bank & FAO, 2018a). The livestock subsector represents 80 percent of Somalia's total exports, which makes this subsector the major contributor to the livelihoods of the people, with 65 percent of the population in some way engaged in this industry. However, the Somali federal government only spends 1.54 percent of its budget on the agricultural sector (Federal Republic of Somalia, 2022). In Somalia, agriculture is not only an important economic activity that meets the population's food needs but also a critical sector in terms of providing labor opportunities and income generation activities through crop sales. Agriculture employs more than 46 percent of all employed people; crop cultivation activities employ 25 percent, 9 percent are involved in herding, the fishery subsector employs 4 percent, and 9 percent are employed in other activities related to agriculture, such as agro-processing and forestry (World Bank & FAO, 2018b).

Climate change has made Somalia one of the world's most vulnerable countries as demonstrated by the past three decades of unpredictable rainfall patterns, rising temperatures, droughts, and floods, compounded by instability that has hindered the mobility of businesses people, especially women. This has negatively affected the agricultural sub-sectors and posed a threat to social economic development. Despite these difficulties, however, the production of crops and livestock continues to be a primary driver of economic activity and a provider of employment and, most significantly, exports. Food imports have surged due to a combination of the collapse of domestic crop production and rising domestic food demand fueled by fast population growth and urbanization. Food imports reached about $1.5 billion in 2015, up from an annual average of $82 million in the late 1980s (World Bank & FAO, 2018b). The absence of short-term and long-term recovery strategies for agricultural production in Somalia increases the vulnerability of the sector. It has been more than four decades since Somalia has seen a scenario like the present drought, which is anticipated to be the country's fifth unsuccessful rainy season in a row (NRC, 2022; OCHA, 2022a). More than 90 percent of the country is now affected by drought conditions ranging from severe to extreme, with 7.1 million people thought to be suffering from severe food insecurity (OCHA, 2022b).

Livestock farming, agriculture, and fisheries are the most important economic sectors in Somalia. About half of Somalia's food needs are fulfilled by domestic production, making the country heavily reliant on agriculture (World Bank & FAO, 2018a). Agricultural production remains the backbone of Somalia's economic development. The agricultural sector is not only important in meeting Somalia's food needs, but it is also important in terms of income-generating activities (IGAs) through crop production, crop sales, and employment opportunities. The Gu season, which lasts from April to June, and the Deyr season, which runs from October to December, are the two primary bi-modal rainfall agricultural seasons in Somalia (SOMALIA: Shocks, agricultural livelihoods and food security – Monitoring report – November 2021). Between 1960 and 1969, Somalia was nearly self-sufficient in terms of crop production. During this period, the southern areas of Somalia were responsible for the production of 88 percent of the country's cereals (Treakle, 1971). Additionally, in the late 1980s, Somalia was almost self-sufficient regarding crop production; however, when the civil war erupted in the 1990s and reached the southern regions, which are Somalia's main agricultural areas, the country developed a chronic food crop deficit (World Bank & FAO, 2018b). Historical records show that pests, droughts, floods, and conflict-related disruptions seriously affected crop cultivation in the southern regions of Somalia from 1995 to 2021 (FEWS-NET & FSNAU, 2022). If Somalia's agricultural sector could be strengthened through increased exports, it would provide better food security and improve employment opportunities for young people. However, the country's susceptibility to drought, floods, and climate change, as well as its low level of productivity, limit this potential (Federal Republic of Somalia, 2022).

According to Treakle (1971), approximately 12.5 percent of the total land area, or approximately 20 million acres, is suitable for cultivation; however, only 1 percent of this land area is cropped. In comparison, approximately 84.6 million acres, or approximately 55 percent of the land area, is used for seasonal grazing and browsing (Treakle, 1971). Over the past three decades, Somalia has been affected by several shocks: civil conflicts, recurrent droughts and floods, locust invasions, and more recently the COVID-19 pandemic that disrupted world economics. Agricultural production studies in Somalia, however, are scarce and insufficient to provide trustworthy information on agricultural productivity. Therefore, the major purpose of this investigation is to analyze the elements that have impacted the agricultural productivity of Somalia between 1991 and 2020. The study used the ARDL approach to cointegration to investigate the agricultural productivity determinants in both the short and long runs. To identify the agricultural productivity determinants, the Cobb-Douglas production function was utilized as the basis for the development of the model. The neoclassical production function (Rowley, 1972) was used as the foundation for the model formulation, allowing an examination of agricultural productivity in Somalia by including macroeconomic variables.

This paper is organized into the following sections: Section 1 has outlined the background of agricultural productivity and the challenges the sector is facing; Section 2 summarizes the theoretical and empirical literature on the subject; Section 3 discusses the study's methodology; Section 4 presents the analysis, findings, and interpretations; finally, Section 5 concludes and offers recommendations.

## 2. LITERATURE REVIEW

Over the years, a lot of research has examined the contributors to agricultural productivity in both developed and developing economies since increasing agricultural productivity by introducing new technologies and encouraging the growth of the agriculture sector to increase its productivity is one of the most important goals of governments whose economies are dependent on agriculture.

Kakar, Kiani, and Baig (2016) conducted research in Pakistan over the period from 1990 to 2017 to determine the factors that influence agricultural productivity. To acquire a reasonable estimate of the multiple determinants, the autoregressive distributed lags (ARDL) technique was applied to get the best possible result. The findings of the research indicated that rainfall, the use of fertilizers, and the availability of agricultural finance all have a favorable impact on agricultural productivity. On the other hand, the findings of the research led the researchers to conclude that the number of people working in agriculture and the usage of pesticides had a positive correlation with agricultural output; however, in the long run, both relationships became statistically less significant. Nevertheless, in the short run, each of the elements had an influence on the rate of agricultural productivity that was both positive and substantial.

Using the ARDL model, Shita, Kumar, and Singh (2018) investigated the variables that affected agricultural productivity in Ethiopia from 1990 to 2016. Using both the error correction model (ECM) and the ARDL bound test for cointegration, they concluded that the variables were cointegrated, meaning that they had a long-term relationship with one another. According to the findings of the study, the production of cereals was significantly impacted in the short and the long run by the use of fertilizers and the real GDP. On the other hand, the research showed that the amount of arable land had a negative influence on agricultural productivity in the short run but a positive impact on productivity in the long run. As a result, the study recommended to the government and other responsible authorities that agricultural technology be made more affordable and available on a timely basis to encourage farmers to accelerate their operations and improve agricultural productivity in Ethiopia.

Gautam and Yu (2015) investigated the factors that led to increases in agricultural productivity in China and India. The paper used data from 1980 to 2008 and 1980 to 2009 in India and China, respectively, to address various research questions using various analytical frameworks. A translog stochastic frontier function allowed for the provision of an estimate of a parametric output-based distance function for China. The parametric method for determining technical characteristics, such as structural bias, was used in the calculation of the productivity growth index as well as the index's many individual components. Using data envelopment analysis, the India study began by analyzing efficiency change, aggregate productivity, and technical change. Finally, a panel regression established a relationship between total factor productivity (TFP) and its determinants. This comparative study revealed several common themes. From the 1980s, the agricultural sector performed well, with yearly growth in China exceeding 2 percent and in India ranging between 1 percent and 2 percent. However, because fewer resources are available and more people are demanding food, the only option to guarantee long-term food security is to boost agricultural output through the use of technological advances. Therefore, the study recommended improving sector technologies in the two countries.

More recently, Andrianarison, Kamdem, and Che Kameni (2022) examined the effects of technological innovation factors on agricultural productivity. To address the potential selection bias, the paper used the Heckman procedure. The paper analyzed the effects of innovation adoption, i.e., modern equipment or seed improvements, and further examined farmers' access to credit, farmers' education, and agriculture land tenure security in Cameroon and their effects on agricultural productivity. The findings of the study were based on an analysis of a national survey that looked at how various innovations and adaptations affected agricultural productivity. According to the findings of the study, agricultural productivity is significantly and positively correlated with innovation adaptations. Farmers' access to credit facilitated the purchase of high-quality pesticides and fertilizers, which increased productivity, while farmers' education increased their potential productivity gains. The study concluded that the adoption of advanced technological equipment alone is insufficient to increase crop output. Therefore, to maximize crop yield, other productivity-enhancing factors ought to be encouraged by the government of Cameroon.

Ketema (2020) studied the determinants of agricultural output in Ethiopia by employing an ARDL approach to cointegration testing. The study made use of a time-series dataset spanning the years 1980 to 2018. According to the findings of the ARDL, the variables of inflation rate, fertilizer input, trade openness, and rainfall all had a positive and substantial effect on agricultural output in Ethiopia in the long run. Ethiopia's agricultural output has suffered immense short-run and long-run losses as a direct result of the ongoing drought that has ravaged the country. In general, the agricultural industry has been hit hard by these losses, which have had a great impact. The paper recommends that the government of Ethiopia focus on sector-relevant policies and use resources wisely, specifically on agricultural expenditure. Additionally, the paper recommends that drought-resistant agricultural mechanisms should be introduced by the government to reduce rainfall dependency by adopting modern agricultural technologies.

## 3. DATA AND METHODOLOGY

### *3.1. Data*

The data is derived from statistics bulletins of yearly time series from the World Development Indicators (WDI), International Labour Organization (ILO), Statistical, Economic and Social Research and Training Centre for Islamic Countries (SESRIC), and the Food and Agricultural Organization Corporate Statistical Database (FAOSTAT), covering the years 1991 to 2020. The investigated variables are agricultural productivity (AP), which is the dependent variable, employment in agriculture (EmA), gross capital formation (GCF), arable land (ArL), and rainfall (RL), which are the independent variables. To analyze the relationships, an autoregressive distributed lags (ARDL) technique was employed.

### *3.2. Theoretical Framework*

To investigate the factors that influence agriculture productivity in Somalia, we looked at four different explanatory variables, namely employment in agriculture (EmA), rainfall (RL), arable land (ArL), and gross capital formation (GCF) as a proxy for machinery adaptation. Based on the available data and the previous literature, these four explanatory variables were chosen because of their expected impact on agricultural productivity. Several empirical studies on the determinants of agricultural productivity have used the Cobb-Douglas production function (Ahmad & Heng, 2012; Ene, Onyele, & Orji, 2022; Shita et al., 2018). Equation 1 models the Cobb-Douglas production function:

$$Y = AK^{\alpha}L^{\beta} \tag{1}$$

Where Y, K, and L indicate output level, capital, and labor inputs, respectively, and A, α, and β are parameters determining the production technology.

The Cobb-Douglas production function analysis considers all the productivity factors, including rainfall, employment in agriculture, gross capital formation, and arable land.

### *3.3. Empirical Model*

Using Equation 2, the coefficients of different factors that are thought to affect agricultural productivity in Somalia are estimated:

$$Ln(AP) = \alpha_0 + \alpha_1 Ln(EmA_t) + \alpha_2 Ln(GCF_t) + \alpha_3 Ln(ArL_t) + \alpha_4 Ln(RF_t) + \varepsilon_t \tag{2}$$

where AP is agricultural productivity, EmA is employment in agriculture, GCF is gross capital formation, ArL is arable land, and RF is rainfall. The long-run coefficients to be estimated are $\alpha_1$ to $\alpha_4$, $\varepsilon$ is the white noise random error, and *t* is the time period.

Numerous econometric tests are available to estimate the long-run relationship between various econometric variables. Many studies have used Johansen and Juselius (1990), Granger and Engle (1987), and Johansen (1988) for cointegration testing. However, in order to employ these cointegration testing techniques, all model variables must be stationary at order 1, that is, they must be I(1). Further, these methods necessitate a large sample size. To avoid these problems, the ARDL approach developed by Pesaran, Shin, and Smith (1996), Pesaran and Shin (1995), and Pesaran, Shin, and Smith (2001) was used in this work since ARDL is flexible and requires that variables are integrated in order 0 or 1. The ARDL has a single requirement, which is that none of the variables in the model can have an order that is I(2) or higher. This is the only condition that must be met. Furthermore, even for small samples, the ARDL estimation technique provides efficient results.

The ARDL technique was chosen for the research because it offers the benefits described above. In addition, some of the variables that were included in the research project are thought to be stationary at level, while others are thought to be stationary at the first difference. These two categories of stability were compared and contrasted. Prior to the development of ARDL estimation techniques, stationary testing was conducted using augmented Dickey-Fuller tests (Dickey & Fuller, 1979). This is significant because practically every macroeconomic time series possesses a unit root, and regression analysis carried out on non-stationary data invariably produces erroneous regression outputs. As a result, the model is written as follows:

$$\Delta Ln\ (AP_t) = \alpha_0 + \sum_{i=1}^{q1} \alpha_{1i} \Delta\ Ln\ (AP_{t-i}) + \sum_{i=1}^{q2} \alpha_{2i} \Delta Ln\ (EmA_{t-i}) + \sum_{i=1}^{q3} \alpha_{3i} \Delta Ln\ (GCF_{t-i}) + \sum_{i=1}^{q4} \alpha_{4i} \Delta Ln\ (ArL_{t-i}) + \sum_{i=1}^{q5} \alpha_{5i} \Delta Ln\ (RF_{t-i}) + \beta_1 \Delta Ln(AP_{t-1}) + \beta_2 \Delta Ln(EmA_{t-1}) + \beta_3 \Delta Ln(GCF_{t-1}) + \beta_4 \Delta Ln(ArL_{t-1}) + \beta_5 \Delta Ln(RF_{t-1}) + \varepsilon_t \quad (3)$$

Where $\Delta$ is the first difference operator, $q1$ represents the optimal lag length, $\alpha_0$ is the drift component, and $\varepsilon_t$ represents the residuals. The coefficients from $\alpha 1$ through $\alpha 5$ represent short-run dynamics, while $\beta 1$ through $\beta 5$ represent the long-run relationships of AP with different explanatory variables.

The first step in ARDL cointegration testing is to conduct bounds testing (Pesaran et al., 2001) for cointegration. This test determines whether or not there is a long-run relationship between the variables that are being researched. This is done to determine whether or not the variables that are being researched are connected to one another in any way. As a consequence, Equation 3 was scrutinized in light of the findings obtained from the bounds testing for cointegration.

The presence of cointegration is presumed if it is discovered that the estimated F-statistic has a value that is higher than the upper bound critical value. On the other hand, an indication that cointegration does not occur is provided when the predicted value of the F-statistic is less than the lower limit. When it is determined that there is cointegration between the variables being studied, an error correction model (ECM) must be constructed. Thus, the ECM results demonstrate how soon convergence occurs following short-run shock, averaging for long-run stability. Equation 4 is used to calculate the ECM:

$$\Delta Ln\ (AP_t) = \alpha_0 + \sum_{i=1}^{q1} \alpha_{1i} \Delta\ Ln\ (AP_{t-i}) + \sum_{i=1}^{q2} \alpha_{2i} \Delta Ln\ (EmA_{t-i}) + \sum_{i=1}^{q3} \alpha_{3i} \Delta Ln\ (GCF_{t-i}) + \sum_{i=1}^{q4} \alpha_{4i} \Delta Ln\ (ArL_{t-i}) + \sum_{i=1}^{q5} \alpha_{5i} \Delta Ln\ (RF_{t-i}) + \delta ECM_{t-1} + \varepsilon_t \quad (4)$$

Where $\delta$ is the speed of adjustment towards equilibrium in the long run, $q1$ is the optimal lag length of the relevant variable, and ECM represents the error correction term. It is anticipated that the coefficient of the error-correction term that is lagged by one period ($ECM_{t-1}$), which is also the speed of adjustment parameter, will have a negative value that is statistically significant, which will provide evidence that a cointegration relationship does, in fact, exist.

### *3.4. Description and Measurement of Variables*

#### *3.4.1. Agricultural Productivity (AP)*

Agricultural productivity is the dependent variable in the model. According to FAO (2017), agricultural productivity is the ratio of output volume to input volume used. Similarly, total factor productivity (TFP) is the amount of agricultural output produced from the whole set of material resources, capital, land, and labor used in farm production, according to the OECD (2017) and USDA (2022).

#### *3.4.2. Employment in Agriculture (EmA)*

The primary determinant of total agricultural productivity is labor. Since land is fixed, increasing agricultural employment increases labor productivity. Employment in agriculture is calculated as a percentage of total employment. As a result, it is reasonable to anticipate that employment activities in agriculture will have a favorable impact on the output of agricultural products.

#### *3.4.3. Gross Capital Formation (GCF)*

GCF includes both the net change in inventories and the money spent on boosting the economy's fixed assets. It is estimated as the total value of a unit's or sector's gross capital formation, inventory changes, and purchases of less valuable disposals.

#### *3.4.4. Arable Land (ArL)*

The average quantity of arable land per person expressed in hectares is what is referred to as "arable land." However, there is not enough evidence to conclude whether a larger amount of land increases agricultural output. Barker and Herdt (1978) argued that large farms outperform smaller ones because they are better able to take advantage of agricultural developments. In contrast, according to Ekbom (1998), the link between farm size and productivity is negative, since small farmers often have to increase output to feed their households. According to estimates provided by the World Bank and FAO (2018a), Somalia possesses 3 million hectares of cultivable land (five percent of Somalia's total land area), of which 2.3 million are rainfed and 700,000 are potentially subject to controlled (pump) irrigation and flood-recession irrigation.

#### *3.4.5. Rainfall (RF)*

Somalia's agricultural economy is heavily influenced by the country's climate, which is measured by rainfall as an indicator of agricultural productivity. The variable is an indicator of yearly precipitation in the country's various agricultural regions and is measured in millimeters. Rainfall and agricultural productivity are expected to have a negative relationship since Somalia is susceptible to climate variability. Recent research by the World Bank suggests that as a direct result of climate change, as many as 216 million people could be compelled to migrate within their own country by the year 2050, and as many as 132 million people could fall into poverty by the year 2030 (Kotikula & Masaki, 2022). Recent cyclical climate-related shocks in Somalia have included drought, flooding, and locust infestations. Climate change may increase Somalia's vulnerability to poverty and food insecurity due to the nation's reliance on natural resources and the deterioration of those resources caused by human activity, such as charcoal manufacture and overgrazing. In Somalia's rural areas, drought has a tendency to significantly restrict consumption, which raises the country's poverty rates. Climate change will have far-reaching consequences for the poor (Kotikula & Masaki, 2022).

## 4. ESTIMATION AND INTERPRETATION OF RESULTS

### *4.1. Unit Root Test*

Time series should be checked for data stationarity before the ARDL technique is applied. Therefore, it is necessary to identify whether or not the data that is being studied is stationary at level, or whether or not it is stationary at the first difference. The ADF unit root test was used to examine the order of integration, and the results are presented in Table 1. All the tested variables (agricultural productivity, employment in agriculture, gross capital formation, and arable land) were stationary at the first difference except the rainfall variable, which was stationary at both the level and the first difference.

**Table 1.** Augmented Dickey-Fuller (ADF) unit root test results at level and first difference.

| ADF test | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Level** | **5% C. values** | **Pro statistic** | **First difference** | **5% C. values** | **Pro statistic** | **Decision** |
| lnAP | -0.032 | -2.989 | 0.956 | -5.099 | -3.588 | 0.000 | I(1) |
| lnEmA | -4.218 | -3.584 | 0.004 | -1.987 | -3.588 | 0.608 | I(1) |
| lnGCF | -0.895 | -2.989 | 0.780 | -4.297 | -3.588 | 0.003 | I(1) |
| lnArL | -2.224 | -2.989 | 0.198 | -2.977 | -1.708 | 0.003 | I(1) |
| lnRF | -4.975 | -2.989 | 0.000 | -3.427 | -2.992 | 0.010 | I(0) & I(1) |

### *4.2. Bounds Test for Cointegration*

The ARDL-based bounds test was considered to answer the question of whether or not there was a relationship between the tested variables in the long run. The findings proved the co-integration between the variables of the model since the estimated value of the F-statistic was 4.62, at a significance level of 5%, which was greater than the upper-bound critical value of 4.01. Table 2 presents the results of the bounds test for cointegration.

**Table 2.** Bounds test for cointegration.

| H0: No levels relationship | | | | | | F-statistic = 4.616 | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | T-statistic = −3.566 | | |
| Critical values (0.1–0.01), F-statistic | | | | | | | | |
| | [I(0)] 10% | [I(1)] 10% | [I(0)] 5% | [I(1)] 5% | [I(0)] 2.5% | [I(1)] 2.5% | [I(0)] 1% | [I(1)] 1% |
| k_4 | 2.45 | 3.52 | 2.68 | 4.01 | 3.25 | 4.49 | 3.74 | 5.06 |

### *4.3. Long-Run Estimation*

Employment in agriculture was significant at the 5 percent level and had a good correlation with agricultural productivity in the long run with a coefficient of 0.55. This outcome is in line with the findings of the FAO (2021) and World Bank and FAO (2018b), who concluded that employment in agriculture accounts for more than 50 percent of Somalia's total workforce. Gross capital formation positively contributed to agricultural productivity. The coefficient value for the influence of GCF on agricultural productivity is 0.6070, which indicates that with all other factors held constant, a one percent increase in GCF results in a 0.6070 percent increase in agricultural productivity. The GCF has the greatest impact on agricultural productivity. Moreover, it also increases labor productivity, thus contributing to an improvement in total agricultural productivity. Also, Table 3 illustrates that arable land significantly and positively affects agricultural productivity. With a coefficient value of 0.162, arable land is the third most important factor in agricultural productivity in this study. This figure indicates that an increase in arable land of 1 hectare will result in a 0.162 percent increase in agricultural productivity. Finally, the analysis showed that rainfall has a negative impact on agricultural productivity but is positively correlated with agriculture. When rainfall increases by one millimeter, agricultural productivity increases by 0.023 percent.

**Table 3.** Estimated long-run coefficients using the ARDL model (dependent variable: LnAP).

| **lnAP** | **Coef.** | **St. err.** | **t-value** | **p-value** | **[95% Conf. interval]** | | **Sig** |
|---|---|---|---|---|---|---|---|
| lnEmA | 0.549 | 0.028 | 19.360 | 0.000 | 0.489 | 0.609 | *** |
| lnGCF | 0.607 | 0.027 | 22.860 | 0.000 | 0.551 | 0.664 | *** |
| lnArL | 0.162 | 0.022 | 7.220 | 0.000 | 0.114 | 0.210 | |
| lnRF | 0.023 | 0.041 | 0.570 | 0.580 | -0.065 | 0.112 | |
| Constant | 3.310 | 0.762 | 4.360 | 0.001 | 1.697 | 4.943 | |
| Mean dependent var | | 20.285 | SD dependent var | | 0.178 | | |
| R-squared | | 0.984 | Number of obs. | | 30 | | |
| F-test | | 392.136 | Prob > F | | 0.000 | | |
| Akaike crit. (AIC) | | -134.098 | Bayesian crit. (BIC) | | -127.092 | | |

**Note:** *** indicates significance at the 10% level.

### *4.4. Short-Run Estimation*

Table 4 shows the short-run and error-correction representations of the chosen ARDL model. Employment in agriculture exhibited a negative association with agricultural productivity in the short run, which was significant at the 5 percent level. This suggests that, in the short run, a one percent increase in agricultural employment reduces agricultural productivity by 3.12 percent. However, a percentage increase in gross capital formation and rainfall enhances agricultural productivity by 0.031 and 0.033 percent, respectively. Furthermore, in the short run, arable land has a negative correlation with agricultural productivity, although this is statistically insignificant. Finally, the stability of the model is indicated by the speed adjustment coefficient's negative sign of -1.025. The model's goodness of fit is further confirmed by the R-squared value of 0.98.

**Table 4.** Estimated short-run coefficients using the ECM approach to the ARDL model (dependent variable: LnAP).

| lnAP | Coef. | St.err. | t-value | p-value | [95% Conf. | interval] | Sig |
|---|---|---|---|---|---|---|---|
| lnEmA | -3.106 | 0.601 | -5.16 | 0.000 | -4.388 | -1.824 | *** |
| lnGFC | 0.031 | 0.021 | 1.06 | 0.308 | -0.032 | 0.094 | *** |
| lnArL | -0.073 | 0.036 | -2.02 | 0.061 | -0.149 | 0.004 | |
| lnRF | 0.033 | 0.017 | 1.97 | 0.067 | -0.003 | 0.069 | |
| $\delta ECM_{t-1}$ | -1.025 | 0.191 | -5.14 | 0.000 | -1.450 | -0.590 | |
| Mean dependent var | | 20.285 | SD dependent var | | 0.178 | | |
| R-squared | | 0.984 | Number of obs. | | 30 | | |
| F-test | | 392.136 | Prob > F | | 0.000 | | |
| Akaike crit. (AIC) | | -134.098 | Bayesian crit. (BIC) | | -127.092 | | |

**Note:** *** indicates significance at the 10% level.

### *4.5. Stability Diagnostic Test (Model Fit)*

In addition to the diagnostic tests mentioned above, an examination of the consistency of the long-run estimations was carried out using the cumulative sum of recursive residuals (CUSUM). The plot of the CUSUM test did not fall outside the critical limits, as shown in Figure 1. The critical boundaries at the 5% significance level are represented by the straight lines.

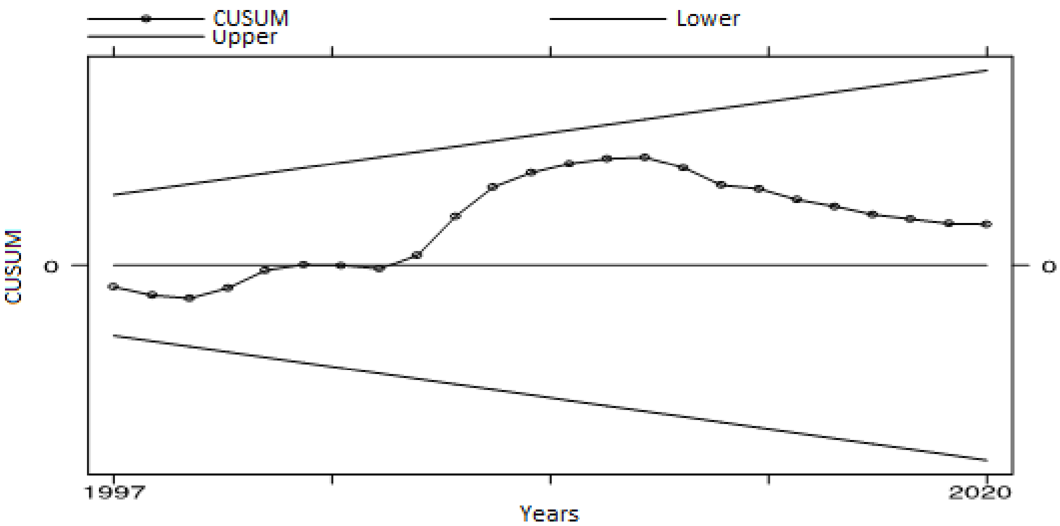


**Figure 1.** Plot of the cumulative sum of recursive residuals.

## 5. CONCLUSION AND RECOMMENDATIONS

In this study, the ARDL methodology was utilized to analyze the determinants that affect agricultural productivity. The research focused on Somalia's agricultural productivity in the period from 1991 to 2020. The results showed that the agriculture productivity level is determined by four explanatory variables: employment in agriculture, gross capital formation, arable land, and rainfall. There is a long-run equilibrium relationship between agricultural productivity, employment in agriculture, gross capital formation, arable land, and rainfall, as indicated by the bounds test and the coefficient of the error correction factor. This can be inferred from the fact that there is a positive correlation between these variables.

Gross capital formation (GCF) is a further major source of total agricultural productivity as it has a positive coefficient value at a 5 percent level of significance, indicating that GCF is the main input increasing agricultural productivity by 0.6070 percent. Moreover, employment in agriculture is an essential determinant of agricultural productivity with a coefficient of 0.5489 and is statistically significant at the 5 percent level. The amount of arable land, which is a very important factor in agricultural productivity, is statistically significant at the 5 percent level and has a positive correlation of 0.1616 with agricultural productivity in the long run; however, in the short run, it has a statistically insignificant negative influence on agricultural productivity. This demonstrates that farmers are experiencing productivity problems, and soil nutrients should be available at low cost and on time, which could facilitate farmers in increasing their productivity by applying soil nutrients.

Lastly, according to the findings of the study, a one-millimeter increase in average rainfall will most likely result in a 0.0233 percent increase in agricultural productivity in the long run, although the effect is statistically insignificant in both the short and long runs. This aligns with the variable description provided in Section 3.4, which stated that rainfall and agricultural productivity are expected to have a negative relationship since Somalia is vulnerable to climate change and the country has experienced extreme weather events over the past 40 years. The result further supports Kotikula and Masaki (2022), who concluded that around 132 million people could fall into poverty due to climate change by the year 2030, including in Somalia. Therefore, farmers and policymakers must consider climate-resilient agricultural practices to mitigate the effects of climate change.

The error correction term of the chosen ARDL model shows a speed adjustment coefficient with a minus sign of -1.025, indicating that the model is stable. The short-run shock model predicts a faster long-run convergence towards equilibrium because the error from the previous time span is addressed in the current time span. The quality of fit of the estimated model is validated by the fact that the R-squared value is 0.98.

Based on the above conclusions, the following policy recommendations are proposed to decision-makers to promote Somalia's agricultural productivity and the sustainable development of its agricultural sector. Firstly, the Somalian government should focus on technological innovations to increase sector productivity. Secondly, Somalia's federal government should increase its expenditure on the agriculture sector, particularly in the areas of education, land tenure security, credit, and the financial accessibility of sector investors. Thirdly, the Somalian federal government should invest more in human capital to promote sustainable productivity growth in the agricultural sector. Fourthly, the study recommends that sector investors support the use of improved agricultural technology, organic fertilizers, and other agricultural extension services that would augment and support agricultural productivity. One limitation of this research is that it has only considered the most important macroeconomic factors that explain agricultural productivity in Somalia. However, fertilizers and agricultural machinery also have an impact on agricultural productivity. As a result, future research may include relevant variables such as fertilizers and agricultural machinery to identify their relationship with agricultural productivity in both the short and long run.

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