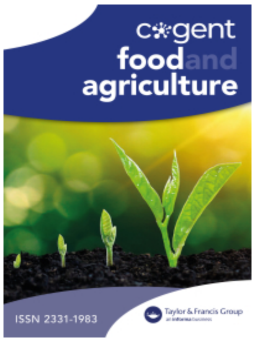


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# Dynamic impacts of economic and environmental performances on agricultural productivity in Somalia: Empirical evidence from ARDL technique

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**ABSTRACT**
This study, conducted using the Autoregressive Distributed Lag (ARDL) technique and Cointegration analysis, explores the dynamic impacts of economic and environmental factors on agricultural productivity in Somalia, spanning from 1990 to 2023. This study incorporates domestic investment, carbon dioxide emissions, rural population growth, and rainfall. The findings, which have significant practical implications, reveal that increasing domestic investment and rural population growth positively influence agricultural output over the long term. This underscores the crucial role of investing in agricultural infrastructure and human capital development. Conversely, higher carbon dioxide emissions negatively impact agricultural productivity, highlighting the urgent need to mitigate climate change effects. Moreover, rainfall emerges as a crucial factor positively affecting agricultural output, emphasizing the importance of water management and conservation efforts. These findings lead to several practical policy recommendations to enhance agricultural productivity in Somalia, including investments in agricultural infrastructure, mitigation of carbon emissions, support for rural development, and promotion of water management and conservation initiatives. Implementing these recommendations can contribute to achieving sustainable agricultural growth, improving food security, and fostering economic development in Somalia, aligning with the objectives of the Sustainable Development Goals.

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## 1. Introduction

Agricultural productivity, a cornerstone in pursuing the Sustainable Development Goals outlined by the 2030 Agenda of the United Nations, is a global concern for food security (Fusco et al., 2023). While agricultural productivity can bolster economic performance, it is equally crucial to comprehend and urgently tackle the associated environmental effects (Ramirez-Contreras et al., 2022). Environmental factors, such as biodiversity, water usage, biomass appropriation, soil degradation, and land conversion, can significantly impact agricultural output (Kastner et al., 2011; Ramirez-Contreras et al., 2022). These studies underscore the importance of avoiding land conversion, optimizing water usage, and enhancing biodiversity to improve agricultural productivity. In many instances, agricultural output is influenced by economic factors, just as environmental factors. According to Owsianiak et al. (2021), Agricultural production hinges on net economic and environmental benefits, which are attainable only when economic and environmental performance are favorable. Agricultural productivity growth is significant, contributing to declining unemployment and poverty (Ayinde et al., 2017). A wide range of infrastructural developments can ensure potential improvements in agricultural productivity in African countries (Edeme et al., 2020). By emphasizing the significance of sustaining a consistently growing agricultural production, both governments and individuals can unlock potential opportunities for national development, and it is widely acknowledged that advancements in the agricultural sector catalyze overall economic progress, which leads to the defeat of unemployment and boost the GPD (Ayinde et al., 2017).

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Ethiopia, one of Africa's most populated countries, has almost 100 million population, of which 80.5% of the rural population relies on agricultural output. Regardless of the population, agricultural productivity is relatively low (Shiferaw, 2017). According to Haile (2004), Overpopulation has given rise to a scarcity of land resources, the fragmentation of farm plots, and the degradation of ecosystems, which are demonstrated by rising emissions, soil erosion, deforestation, and excessive exploitation of natural resources. On the other hand, Sub-Saharan Africa has been identified as the region most vulnerable to the consequences of global climate change due to its heavy dependence on agriculture, which exhibits high sensitivity to weather variables, notably rainfall and light (Kotir, 2011). Barrios et al. (2008) Similarly, the climate has been a significant factor in Sub-Saharan Africa's (SSA's) agricultural production, as evidenced by variations in national rainfall. Although Farmers can utilize other irrigation techniques such as solar tube wells, using technology, and tunnel farming, all of which have an impact on agricultural productivity (Magazzino et al., 2023). Carbon emissions are the main gaseous substances released into the atmosphere because of human activities like burning fossil fuels. Carbon dioxide emissions have a negative impact on agricultural productivity (Matthew et al., 2020).

Agriculture serves as the backbone of Somalia's economy, providing livelihoods for the majority of its population and contributing significantly to its GDP. Despite its importance, agricultural productivity in Somalia has faced persistent challenges over the years, characterized by fluctuating trends due to various environmental and socio-economic factors. Historically, agriculture has been the backbone of Somalia's economy, contributing significantly to GDP and employing a large portion of the population. However, recent decades have seen a decline in productivity due to persistent droughts, political instability, and inadequate infrastructure. Somalia's agricultural sector is heavily dependent on seasonal rainfall, making it vulnerable to climatic variability. According to Warsame et al. (2021), the rainfall had a positive long-term effect on agriculture but a negative short-term effect due to the immediate disruptive impacts of erratic weather patterns. On the other hand, Samatar (2023) Employed the ARDL model to investigate the determinants of agricultural productivity in Somalia and found that rural populations have both short-term and long-term impacts on agricultural productivity in Somalia. Furthermore, in Somalia, 75 percent of the GDP, in the most general sense, is compensated by agricultural production (MOP Somalia, 2020). Agriculture also contributes considerably to the Somali economy (GDP) by producing 93% of all export revenue (Warsame et al., 2021). Population expansion plays a significant role in total economic growth and, in some situations, may even increase growth in per capita output. Somalia is considered a low-income country, and rapid population growth is expected to negatively impact the country in the short term due to the large number of dependent children. However, population growth may positively affect productivity and the general economy in the long run as the younger generation becomes productive adults (Peterson, 2017).

Therefore, this study aims to ascertain the dynamic impact of the economy and environment on agricultural productivity in Somalia by assessing economic variables, gross domestic product (GDP), Unemployment, rural population growth, environmental variables, carbon dimensions (CO2), and rainfall. By combining the effect of these variables on agricultural production in Somalia, a context that has yet to be extensively studied, this study contributes to the existing literature.

The rest of the study is organized as follows. Section 2 provides an overview of relevant studies. Section 3 outlines the data collection process and econometric models employed. Section 4 presents the empirical findings and discussions. Section 5 concludes the paper and recommends relevant policy implications.

## 2. Literature review and hypotheses development

This study investigates the interaction of domestic investment, CO2 emissions, rural population growth, and rainfall, constituting a complex set of factors influencing agricultural output. The literature review of this study synthesizes existing research on these primary strands influencing agricultural output. The first strand of the literature assesses the impact of Domestic investment (DI) on agricultural production. Domestic investment improves agricultural productivity by facilitating efficient resource allocation and market access. Research by Baylis et al. (2019) and Shamdasani (2021) shows that domestic investment reduces post-harvest losses, enhances value chain efficiency, and fosters agricultural productivity growth by connecting farmers to markets and enabling timely access to inputs and information. Domestic investments contribute to human capital development among farmers, extension workers, and agricultural professionals, enhancing agricultural productivity. Laborde et al. (2019) highlight that domestic investments in education and extension services improve farmers' knowledge, skills, and decision-making abilities. This leads to increased adoption of productivity-enhancing technologies and sustainable farming practices. Domestic investments contribute to sustainable agricultural productivity by enhancing soil fertility, water-use efficiency, and resilience against environmental degradation. Besley (1995) and Gedefaw (2023) argue that targeted domestic investments in land management and conservation practices improve land productivity, mitigate land degradation, and promote sustainable intensification of agricultural production systems. Domestic investments are critical in mobilizing investment incentives and institutional support mechanisms, improving resource allocation efficiency, and promoting innovation and entrepreneurship in the agricultural sector. Improving domestic investment can enhance agricultural productivity, promote subsidies to people experiencing poverty, and encourage regional and global cooperation to ensure food security for the world's growing population (ADB, 2011).

**H1:** A significant Positive relationship exists between domestic investment and Agricultural output.

The second strand of the literature assesses the impact of CO2 emissions on agricultural output. Indeed, Since the economy's growth depends on all its sectors, every sector, including agriculture, directly or indirectly impacts CO2 emissions (Ullah et al., 2021). It is well known that agricultural productivity, carbon emissions, and subsequent climate change are related (Zhou et al., 2022). An expanding body of empirical studies assessed the impact of $CO_2$ emissions on Agricultural output. For instance, Edoja et al. (2016) Using time series econometrics, they examined the dynamic link between $CO_2$, agricultural productivity, and food security from 1961 to 2010. The results show a long-term association and a one-way causal relationship between $CO_2$ and food security. Chopra et al. (2022) Examined how renewable energy and natural resources impact sustainable agriculture in ASEAN countries, highlighting the adverse effects of carbon emissions and deforestation on agricultural productivity. This research emphasizes the critical role of sustainable energy solutions in mitigating environmental damage and enhancing agricultural output. In contrast, Valin et al. (2013) Also, partial econometric analysis will be used to analyze the adverse effects of climate change on agricultural production. Additionally, according to the results of Eshete et al. (2020) Utilizing a dynamic, computational, recursive general equilibrium model to investigate the impact of CO2 emissions on agricultural performance and household welfare reveals that CO2 emissions have a negative effect on teff, maize, and wheat, which are traded and non-traded agricultural products in Ethiopia. Therefore, the following hypothesis is proposed:

**H2**: There is a significant negative relationship between CO2 emissions and Agricultural output.

The third strand of the literature assesses the impact of rural population growth on agricultural production. Since 2008, rural populations in less developed countries have been growing faster than developed countries, gaining national attention for the first time (Anríquez & Stloukal, 2008). However, in some nations in Central America, rural populations continue to decrease (Carr et al., 2009). The majority of research indicates that an increase in rural population has a significant impact on agricultural output. For example, Ioffe and Nefedova (2018) examined the effects of rural population change on agriculture. They found that changes in rural population demographics significantly affect agricultural systems, land use patterns, and farming practices. A study conducted by Ge et al. (2020) investigated the effects of rural-urban migration on agricultural transformation in Yucheng City, China. The study found that migration from rural to urban areas leads to a decrease in the rural labor force available for agricultural activities, affecting agricultural production and land use patterns. These findings indicate that the rural population positively impacts agricultural output in China. Adaku (2013) found similar results in Ghana. Agriculture is the primary industry in rural areas. A large portion of the rural population works in agriculture, either directly or indirectly. The expansion of agriculture is affected by rural residents' social well-being, way of life, environmental quality, and economic development. Noted that, at the national level, agricultural laborers somewhat outnumber cultivators regarding the total number of people employed in rural areas. On the other hand, Sohns and Revilla Diez (2018) concluded that rural residents supply the labor force required to carry out various agricultural tasks such as crop cultivation and livestock breeding, and they ensure the supply of these products for the benefit of rural society and the economy. Therefore, it is hypothesized that the agriculture industry's ability to survive and expand is influenced by the size of the rural population overall or its rate of expansion. When there is a large population in rural areas, many human resources are available to support agriculture and ensure its expansion, ultimately resulting in the prosperity and welfare of rural communities. Therefore, the following hypothesis is proposed:

**H3:** A significant positive relationship exists between rural population growth and Agricultural output.

The fourth strand of the literature assesses the impact of rainfall on agricultural output. An expanding body of empirical studies evaluated the effect of rainfall on agrarian output (Amare et al., 2018; Hussain et al., 2020; Talib et al., 2021). According to the study by Nyirenda and Sachikumba (2019) Revealed that the decrease in annual rainfall may negatively impact groundwater recharge, soil moisture content, surface water resources, and agricultural productivity, especially rain-fed agriculture in Zambia. Similarly, Wang et al. (2009) Analyzed the potential for supplying the water needed for crops under rainy conditions based on the best time to plant in SSA to take advantage of the favorable weather. They confirmed that Rainfall was the most significant factor in the agricultural productivity of Burkina Faso and Malawi. This shows how important it is to manage rainfall water to increase productivity, especially in low-productive areas. Additionally, Bessah et al. (2021) Evaluated, for the first time, the performance of the statistical downscaling model (SDSM-DC) at 2 m spatial resolution in simulating rainfall in Ghana for the base period 1981–2010. It was discovered that even the slightest change in rainfall could significantly impact rain-fed agriculture in nations like Ghana. While Olayide et al. (2016) utilized time series To evaluate the varied effects of rainfall and irrigation on agricultural production by aggregate and sub-sectors, including all crops, staples, livestock, fisheries, and forestry. They employed data spanning from 1970 to 2012. It was discovered that irrigation positively and significantly impacted total agricultural production and all sub-sectors of agriculture. In contrast, rainfall had a positive but insignificant impact on total agricultural production and all sub-sectors of agriculture. Therefore, the following hypothesis is proposed:

**H4**: There is a significant positive relationship between rainfall and Agricultural output.

The literature review discussed four research hypotheses to investigate how domestic investment, CO2 emissions, rural population growth, and rainfall influence agricultural output. The first hypothesis posits a significant positive relationship between domestic investment and agricultural production, highlighting the pivotal role of investment in infrastructure, technology, and human capital in enhancing productivity and sustainability in agriculture. In contrast, the second hypothesis suggests a significant negative relationship between CO2 emissions and agricultural output, emphasizing the detrimental effects of climate change on agricultural productivity. The third hypothesis proposes a significant positive relationship between rural population growth and agricultural production, underscoring the importance of rural labor force availability for sustaining and expanding agricultural activities. Finally, the fourth hypothesis suggests a significant positive relationship between rainfall and agricultural output, emphasizing the critical role of water availability, whether through rainfall or irrigation, in enhancing agricultural productivity. Since no study uses the effect combination of these variables on agricultural production in Somalia. The gap our study tries to fill is how these factors affect agricultural productivity in the context of Somalia. This study has illustrated the conceptual design in Figure 1 to map the relationships between the dependent variable (agricultural output) and the explanatory variables (domestic investment, rural population growth, carbon dioxide emissions, and rainfall). The arrows in the diagram represent the hypothesized directional influences of each variable on agricultural output.

## 3. Methodology

### 3.1. Data

This study uses annual time series data from 1990 to 2023 to analyze the effects of economic and environmental factors on agricultural output in Somalia. The study period was determined based on data availability for all variables. The dependent variable of this study is agricultural production, while domestic Investment (DI), rural population growth (UPG), carbon dioxide emissions (CO2), and rainfall (RF) are the explanatory variables. The data was obtained from the World Bank, FAO, and the Organization of Islamic Cooperation countries (OIC) database SESRIC. See Table 1 for more about the data sources and measurements. This utilized EViews 12, a comprehensive econometric software package, for all our data analysis and econometric modeling. This software was chosen for its robust capabilities in handling advanced econometric techniques and diagnostic tests (Markit, 2020), ensuring the reliability and validity of our results.

### 3.2. Econometric methods

In this study, agricultural output is linked to economic and environmental variables. Economic variables are domestic investment and rural populations, while

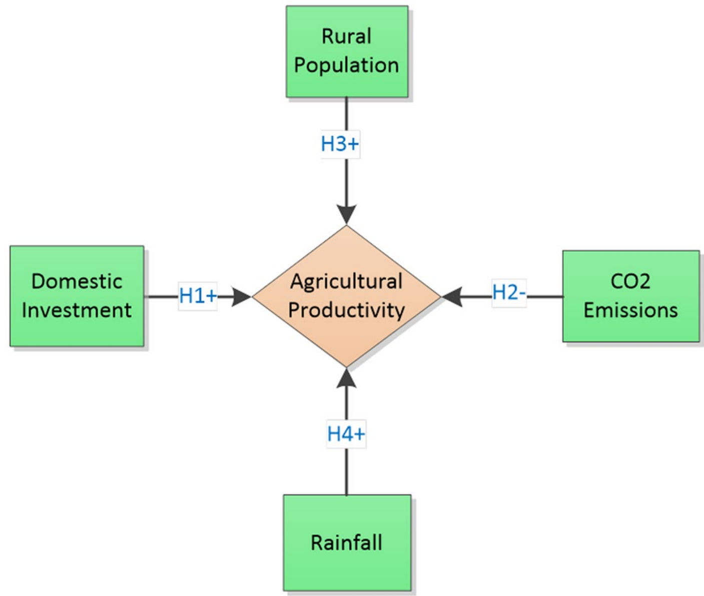


**Figure 1.** Hypothesis Framework.

**Table 1.** Description and sources of variables.

| Symbols | Variables | Measurements | Sources |
|---|---|---|---|
| AO | Agricultural output | Total agriculture output | FAO |
| DI | Domestic Investment | Gross Fixed Capital Formation, Current Prices | SESRIC |
| RPG | Rural population | Rural population growth | World Bank |
| CO2 | Carbon emissions | Kilotons | World Bank |
| RNFL | Average Rainfall | Total annual rainfall for the nation | SESRIC |

carbon dioxide emissions and rainfall represent environmental variables. The empirical model posits that agricultural output (AO) is a function of these economic and environmental variables. To identify the linkage between agricultural output and explanatory variables such as domestic investment, rural populations, carbon dioxide emissions, and rainfall, This study uses the following model – by employing the previous studies (Otim et al., 2023; Pickson & Boateng, 2022).

$$AO_t = \beta_0 + \beta_1 CO2_t + \beta_2 DI_t + \beta_3 RP_t + \beta_4 RF_t + \varepsilon_t AO_t + \varepsilon_t \quad (1)$$

where $\beta_0$ is the model intercept, $\beta_{1\text{-}4}$ are the coefficients that measure how explanatory variables influence the dependent variable, while $\varepsilon_t$ donates the error term. Moreover, to avoid heteroscedasticity and autocorrelation, we transform our model into logarithmic (Akgiray, 1989; Bates & Campbell, 2001; Evin et al., 2014; Warsame et al., 2022), and it is written as:

$$LAO_t = \beta_0 + \beta_1 LCO2_t + \beta_2 LDI_t + \beta_3 LRP_t + \beta_4 LRF_t + \varepsilon_t \quad (2)$$

where LAO is the natural logarithmic form of agricultural output at time t, LCO2 is the natural logarithmic form of carbon dioxide emissions at time t, LDI is the natural logarithmic form of domestic investment at time t, LRP is the natural logarithmic form of rural population growth at time t, and LRF the natural logarithmic form of is the rainfalls at time t.

The study utilizes the Autoregressive Distributed Lag (ARDL) model, which was introduced by Pesaran et al. (2001) and is more effective than earlier cointegration approaches (Menyah & Wolde-Rufael, 2010; Panopoulou & Pittis, 2004). The ARDL model is suitable for analyzing the long-run relationships and short-run dynamics between variables. The unit root test was utilized to verify that no variable exceeded the order of integration, which is crucial to avoid incorrect regression (Dickey & Fuller, 1979). The ARDL model allows for including stationary and non-stationary variables in the analysis to ensure that we use the ADF unit root test for stationarity, making it suitable for time series data. The ARDL model used in the study can be expressed as follows:

$$\begin{aligned} \Delta LAO_t = {} & \alpha_0 + \beta_1 LAO_{t-1} + \beta_2 LCO2_{t-1} \\ & + \beta_3 LDI_{t-1} + \beta_4 LPR_{t-1} + \beta_5 LRF_{t-1} \\ & + \sum_{i=1}^{p} \alpha_1 \Delta LAO_{t-i} + \sum_{i=1}^{p} \alpha_2 \Delta LCO2_{t-i} \\ & \sum_{i=1}^{r} \alpha_3 \Delta LDI_{t-i} + \sum_{i=1}^{q} \alpha_4 \Delta LRP_{t-i} + \sum_{i=1}^{v} \alpha_5 \Delta LRF_{t-i} + \varepsilon_t \end{aligned} \quad (3)$$

where $\Delta$ represents the first difference of the short-term variables, $\alpha_0$ is the intercept term, $\alpha_{1\text{-}5}$ and $\beta_{1\text{-}5}$ are the coefficients of the lagged differences of long-run and short-run variables, respectively, $\varepsilon_t$ represents the error term. The ARDL model is estimated using the Ordinary Least Squares (OLS) method. After obtaining the coefficients, the long-run and short-run relationships between the variables can be analyzed. Additionally, this study employs Fully Modified OLS (FMOLS), Dynamic OLS (DOLS), and Canonical Cointegrating Regression (CCR) to validate the long-run results from the ARDL model, similar to previous studies (Adebayo et al., 2021; Hussein et al., 2023; Pattak et al., 2023).

## 4. Empirical analysis and discussion

### 4.1. Descriptive statistics

The descriptive statistics in Table 2 provide valuable insights into the distribution and characteristics of five variables: LAO, LCO2, LDI, LRF, and LRP. The mean values reflect the average level of each variable, with LAO having the highest mean of 7.255 and LRP having the lowest at 4.127. The median values, which represent the middle point of the data, are similar to the means, indicating symmetric distributions. The range between all variables' maximum and minimum values is relatively narrow, suggesting limited dispersion. Standard deviation measures the degree of dispersion around the mean, with LDI exhibiting the highest variability (0.732) and LAO the lowest (0.024). Skewness and kurtosis provide insights into the shape of the distributions. Negative skewness in LAO and LCO2 suggests a slight leftward skew, while positive skewness in LDI, LRF, and LRP indicates a slight rightward skew. Kurtosis values around 3 for most variables suggest distributions close to normal, with LRP showing a slightly flatter distribution. The Jarque-Bera test assesses the normality of the data. All variables have $p$-values above 0.05, indicating significant deviation from normality. Moving to the correlation matrix at the bottom of the Table, it is apparent that there are some relationships between the variables. LAO and LCO2 exhibit a very weak negative correlation (approximately −0.01955), indicating a slight tendency for these variables to move in opposite directions, though the correlation is insignificant. LRF and LRP show a weak negative correlation (approximately −0.08579), suggesting a slight inverse relationship. LDI demonstrates a moderate positive correlation with LAO (0.042035) and a strong negative correlation with LRP (-0.8855), indicating a significant tendency for LDI to move in the opposite direction of LRP. The descriptive statistics and correlations offer a comprehensive overview of the variables' characteristics and relationships, providing valuable insights for further analysis and interpretation in the relevant context.

### 4.2. ADF unit root test

The concept of stationarity holds significant importance in time series analysis, as non-stationary series can display patterns or cycles that might introduce misleading outcomes in statistical examinations. There are many tests used in stationarity. This study uses the Augmented Dickey-Fuller (ADF) unit root test, which was introduced by Dickey and Fuller (1979). The ADF unit root test results presented in Table 3 assess the stationarity of various variables at both levels and first differences, with two model specifications: with constant and with constant and trend. At the level, the variables agricultural output, $CO_2$ emissions, domestic investment, and rural populations have t-statistics that do not reach the critical values for rejecting the null hypothesis of a unit root, indicating non-stationarity, as evidenced by their high $p$-values (greater than 0.05). The exception is the rainfall variable, which shows significant t-statistics (−4.840 and −6.913) and $p$-values (0.000) in

**Table 2.** Descriptive statistics.

| Variables | LAO | LCO2 | LDI | LRF | LRP |
|---|---|---|---|---|---|
| Mean | 7.255 | 6.412 | 6.289 | 5.630 | 4.127 |
| Median | 7.256 | 6.432 | 6.196 | 5.629 | 4.156 |
| Maximum | 7.313 | 6.600 | 7.901 | 5.854 | 4.253 |
| Minimum | 7.197 | 6.187 | 4.846 | 5.439 | 3.953 |
| Std. Dev. | 0.024 | 0.095 | 0.732 | 0.098 | 0.097 |
| Skewness | −0.148 | −0.617 | 0.215 | 0.243 | −0.375 |
| Kurtosis | 3.247 | 3.157 | 2.659 | 3.071 | 1.700 |
| Jarque-Bera | 0.210 | 2.192 | 0.427 | 0.342 | 3.193 |
| Probability | 0.900 | 0.334 | 0.808 | 0.843 | 0.203 |
| Correlation | | | | | |
| LAO | 1 | | | | |
| $LCO_2$ | −0.01955 | 1 | | | |
| LRF | −0.08579 | 0.038247 | 1 | | |
| LRP | −0.08915 | −0.2569 | −0.51721 | 1 | |
| LDI | 0.042035 | −0.00037 | 0.59784 | −0.8855 | 1 |

both models, suggesting stationarity at the level. When first differenced, all variables exhibit significant t-statistics and low *p*-values (less than 0.05), indicating the rejection of the null hypothesis of a unit root. This implies that these variables are stationary after differencing once. Overall, the ADF test results indicate that, except for rainfall, the variables are non-stationary at their levels but become stationary after first differencing. This implies that the process of differencing results in the stationarity of all variables, a desired characteristic for doing time series analysis.

### 4.3. Long-run cointegration test

The F-bounds test is a statistical tool to evaluate the long-term relationship between dependent and explanatory variables. The results presented in Table 4 assess how important the independent variables (LCO2, LDI, LRF, and LRP) are in explaining the dependent variable (AO) in the long term. This test helps us understand if including these variables significantly improves the model's explanatory power. We compare the F-statistic, with a value of 9.055, to critical values at different significance levels (1%, 5%, and 10%). The significance levels indicate the likelihood of detecting a significant F-statistic, assuming all coefficients are zero. The analysis shows that the collective impact of the independent variables is statistically significant, with the F-statistic being higher than the critical values at all three significance levels.

**Table 3.** ADF unit root test results.

| At level | | | | |
|---|---|---|---|---|
| | With constant | | With constant & trend | |
| Variables | *t*-Statistic | Prob | *t*-Statistic | Prob |
| LAO | −2.732 | 0.081 | −2.544 | 0.307 |
| LCO2 | −2.088 | 0.251 | −2.591 | 0.286 |
| LDI | −0.580 | 0.862 | −2.727 | 0.233 |
| LRF | −4.840 | 0.000 | −6.913 | 0.000 |
| LRP | 0.925 | 0.995 | −1.937 | 0.613 |
| At first difference | | | | |
| Variables | *t*-Statistic | Prob. | *t*-Statistic | Prob. |
| d(LAO) | −4.699 | 0.001 | −4.585 | 0.005 |
| d(LCO2) | −3.628 | 0.011 | −3.639 | 0.042 |
| d(LDI) | −5.521 | 0.000 | −5.268 | 0.001 |
| d(LRF) | −10.905 | 0.000 | −10.713 | 0.000 |
| d(LRP) | −5.301 | 0.000 | −5.497 | 0.001 |

This indicates that the variables are integrated of order I(0) and I(1) or have a unit root. The results of the F-Bounds test reflect the statistical significance of the model that uses LCO2, LDI, LRF, and LRP as predictors of AO. This model provides valuable insights into how these variables are associated with AO.

### 4.4. ARDL results

The Autoregressive Distributed Lag (ADL) findings, as displayed in Table 5, provide significant insights into long -and short-run associations among the variables examined in this Study. In the long run, the coefficients provide insights into the association between the dependent variable (Agricultural Output) and the independent variables. The carbon dioxide and rainfall coefficients demonstrate statistical significance, with negative (−0.072) and positive (0.121) at a 0.05 significance level. This observation suggests that in the long run, a marginal increase of one percent in carbon dioxide reduces the Agricultural output by 7%. In contrast, a marginal increase of one percent in rainfall increases agricultural production by 12%. At standard levels, the coefficient for the rural population exhibits statistical significance positive association (0.034) at a 0.1 significance level, indicating that the rural population growth in Somalia substantially impacts Agricultural output by 3.4% in the long term. The coefficient for domestic investment exhibits a marginally significant positive relationship (0.023) at a significance level of 0.05. This suggests that an upward trend in domestic investment is associated with a modest increase in Somalia's agricultural output by 2.3% in the long term.

The ECM (−1) coefficient reflects how quickly a system adjusts towards its long-term equilibrium after a shock. A significant and negative coefficient (−2.133) indicates that the system is adjusting towards its equilibrium, with deviations from the equilibrium being corrected over time. In the short run, the coefficients of D(LCO2) and D(LDI) variables positively relate to Agricultural output in Somalia, indicating that increases in C02 emissions and domestic investments result in short-term increases in agricultural production by 43% and 3.6%, respectively. Conversely,

**Table 4.** F-bounds test.

| Model: AO = *f*($LCO_2$, LDI, LRF,LRP) | | | K = 4 | |
|---|---|---|---|---|
| Test Statistic | Value | Significant | I(0) | I(1) |
| F-statistic | 9.055204 | 1% | 3.74 | 5.06 |
| | | 5% | 2.86 | 4.01 |
| | | 10% | 2.45 | 3.52 |

Note: Null Hypothesis: No long-run levels of relationship, K represents the number of parameters.

**Table 5.** ARDL results.

| | Long run | | | |
|---|---|---|---|---|
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
| LCO2 | −0.072 | 0.025 | −2.911 | 0.023 |
| LRF | 0.121 | 0.044 | −2.736 | 0.029 |
| LRP | 0.034 | 0.069 | 0.487 | 0.641 |
| LDI | 0.023 | 0.010 | 2.328 | 0.053 |
| ECM (-1) | −2.133 | 0.253 | −8.435 | 0.000 |
| Short Run | | | | |
| D(LCO2) | 0.430 | 0.079 | 5.450 | 0.001 |
| D(LRF) | −0.090 | 0.022 | −4.031 | 0.005 |
| D(LRP) | 0.640 | 0.246 | −2.604 | 0.035 |
| D(LDI) | 0.036 | 0.008 | −4.543 | 0.003 |
| C | 17.270 | 2.047 | 8.435 | 0.000 |
| $R^2$ | 0.952 | | | |

the negative coefficient of rainfall suggests that an increase in LRF leads to a decrease in Agricultural output in the short run by 9%. The statistical significance of the intercept term (C) suggests that it represents the baseline level in agricultural production when all independent variables are set to zero. Lastly, the coefficient of determination ($R^2$) is 0.952, suggesting that the model explains 95.2% of the variation in the dependent variable.

### 4.5. Diagnostic test

According to the results of the diagnostic check in Table 6, the Normality test value is 0.411, with an associated probability of 0.814, indicating that the model errors are normally distributed. The heteroscedasticity test value is 5.965, with a probability of 0.734, suggesting no significant evidence of heteroscedasticity in the model. The autocorrelation test value is 0.871, with a probability of 0.647, indicating no evidence of serial correlation in the errors. The Ramsey RESET test value is 0.812, with an associated probability of 0.378, suggesting no significant evidence of omitted variables in the model. Based on these comprehensive diagnostic results, we can confidently conclude that the model of this study is more reliable.

### 4.6. Cointegration estimations analysis

The results presented in Table 7 show the coefficients and associated probabilities of FMOLS, DOLS, and CCR, which analyze the long-run relationships between the economic and environmental factors and agricultural output. In FMOLS, the coefficient for carbon dioxide emission is estimated at −0.064, indicating that a 1% increase in $CO_2$ emissions leads to a decrease of 0.064% in agricultural output. Similarly, the coefficients for domestic investment, rainfall, and rural population in FMOLS are 0.005, 0.117, and 0.106, respectively, suggesting positive impacts on agricultural output. The coefficients in DOLS and CCR generally follow a similar pattern to FMOLS but with slightly different magnitudes. For instance, the coefficient for CO2 emissions is estimated at −0.216 in DOLS and −0.072 in CCR, indicating a significant negative impact on agricultural output, consistent with FMOLS. The coefficients for domestic investment, rainfall, and rural population also indicate stronger positive impacts on agricultural production in Somalia in both DOLS and CCR, similar to FMOLS. These robust cointegration estimators highlight the long-run relationships between economic and environmental factors and agricultural output in Somalia. The high R-squared values (0.962 for FMOLS, 0.985 for DOLS, and 0.972 for CCR) suggest that these models explain a substantial portion of the variability in the agricultural output using the economic and environmental factors, indicating the robustness of the cointegration estimators in capturing the long-run relationships among the variables.

**Table 6.** Diagnostic check.

| Diagnostic check | Value | Probability |
|---|---|---|
| Normality Test | 0.411 | 0.814 |
| Heteroscedasticity test | 5.965 | 0.734 |
| Autocorrelation LM test | 0.871 | 0.647 |
| Ramsey RESET test | 0.812 | 0.378 |

**Table 7.** FMOLS, DOLS, and CCR results.

| | FMOLS | | DOLS | | CCR | |
|---|---|---|---|---|---|---|
| Variable | Coefficient | Prob | Coefficient | Prob | Coefficient | Prob |
| LCO2 | −0.064 | 0.000 | −0.216 | 0.008 | −0.073 | 0.000 |
| LRF | 0.117 | 0.000 | 0.262 | 0.003 | 0.250 | 0.000 |
| LRP | 0.106 | 0.000 | 0.701 | 0.024 | 0.126 | 0.000 |
| LDI | 0.005 | 0.097 | 0.101 | 0.019 | 0.014 | 0.000 |
| C | 8.733 | 0.000 | 9.374 | 0.000 | 9.562 | 0.000 |
| $R^2$ | 0.962 | | 0.985 | | 0.972 | |

### 4.7. Results discussion

Our study revealed a positive long-run relationship between domestic investment and agricultural output, indicating that increasing domestic investment likely improves access to agricultural inputs, technologies, and infrastructure, thereby boosting productivity. This finding aligns with Edeme et al. (2020), which emphasized the importance of infrastructure and investment in enhancing agricultural productivity in African countries. Additionally, the study found a long-run negative relationship between carbon dioxide (CO–) emissions and agricultural output, suggesting that higher CO2 levels exacerbate climate change impacts, adversely affecting crop yields in the long run. This result is consistent with Matthew et al. (2020), who reported a detrimental effect of CO2 emissions on agricultural productivity in West Africa. Conversely, rainfall (RF) shows a positive long-run impact on agricultural output, underscoring the crucial role of adequate rainfall in sustaining agricultural productivity. This finding aligns with Warsame et al. (2021), who found that increased rainfall positively affects agricultural production in Somalia. Moreover, rural population growth (RP) demonstrates a positive long-run relationship with agricultural output, indicating that an increasing rural population contributes to higher agricultural output. This supports Peterson (2017), who highlighted the potential for rural population growth to drive agricultural productivity through increased labor availability and farming activities.

In the short run, the positive effect of D(LCO2) on agriculture suggests that CO2 emissions temporarily boost agricultural output, possibly due to the fertilization effect of CO2 on plant growth. However, this short-term gain is likely offset by long-term climatic changes. Similar short-term positive effects of CO2 have been documented in some studies (Mendelsohn & Rosenberg, 1994). The short-run positive impact of domestic investment on agricultural output further underscores the immediate benefits of capital inflows into the agricultural sector. This finding is consistent with Shamdasani (2021), who observed that immediate increases in agricultural investment lead to productivity gains. On the other hand, rainfall exhibits a negative short-run impact on agricultural output, reflecting the immediate disruptive effects of excessive or insufficient rainfall, as noted by Schmidhuber & Tubiello (2007), who observed short-term volatility in agricultural yields due to weather extremes. The results from the cointegration estimations (FMOLS, DOLS, and CCR) robustly confirm the long-run relationships identified in the ARDL model. The negative coefficients for carbon dioxide emissions across all estimators reinforce the detrimental long-term impact of CO2 emissions on agriculture. In contrast, the positive coefficients for domestic investment, rainfall, and rural populations highlight their beneficial effects on agricultural production. Our findings are consistent with and add to the existing body of literature. For instance, the negative impact of CO2 on agricultural output aligns with the results of (Matthew et al., 2020; Owsianiak et al., 2021), while the positive role of rainfall corroborates (Kotir, 2011; Warsame et al., 2021). The positive effects of rural population growth and domestic investment support the conclusions drawn by Ayinde et al., (2017; Edeme et al., 2020).

The analysis of this study is anchored in hypotheses from a literature review examining the relationship between variables such as domestic investment, CO2 emissions, rural population growth, and rainfall on agricultural output. Let's discuss how the hypotheses proposed in the study align with the findings and the broader literature review. The first hypothesis (H1) suggests a positive relationship between domestic investment and agricultural output. The study's findings support this hypothesis, indicating a positive association between domestic investment and agricultural output in Somalia. This aligns with the existing literature (Baylis et al., 2019; Gedefaw, 2023; Laborde et al., 2019; Shamdasani, 2021) that emphasizes the importance of domestic investment in enhancing agricultural productivity through improved infrastructure, technology adoption, and human capital development among farmers. The second hypothesis (H2) suggests a negative relationship between $CO_2$ emissions and agricultural output. The study's results confirm this hypothesis, demonstrating a negative impact of $CO_2$ emissions on agricultural output in Somalia. This finding resonates with previous research (Edoja et al., 2016; Eshete et al., 2020; Valin et al., 2013; Zhou et al., 2022) that highlights the detrimental effects of carbon emissions on agricultural productivity, leading to reduced crop yields and overall output. The third hypothesis (H3) suggests a positive relationship between rural population growth and agricultural output. The analysis supports this hypothesis by revealing a positive association between rural population growth and agricultural output in Somalia. This finding is consistent with the literature (Adaku, 2013; Ge et al., 2020; Ioffe & Nefedova, 2018; Ramirez-Contreras et al., 2022), which suggests that an expanding rural population can contribute to increased agricultural production through labor availability and expansion of the agricultural sector. The fourth hypothesis (H4) suggests a positive relationship between rainfall and agricultural output. The study's results uphold this hypothesis, indicating a positive relationship between rainfall and agricultural output in Somalia. This aligns with existing research (Bessah et al., 2021; Nyirenda & Sachikumba, 2019; Olayide et al., 2016; Talib et al., 2021) that underscores the crucial role of rainfall in determining agricultural productivity, particularly in rain-fed agricultural systems like those prevalent in Somalia.

The study's findings provide empirical evidence that corroborates the hypotheses derived from the literature review. By employing the ARDL technique and analyzing a comprehensive set of economic and environmental variables, the study offers valuable insights into the dynamic impacts of these factors on agricultural productivity in Somalia. It highlights the importance of sustainable development strategies in mitigating climate risks and fostering agrarian growth. Furthermore, these findings contribute to the existing knowledge of agricultural development in Somalia. Unlike other studies, this research examined the contributions of $CO_2$ emissions, domestic investment, rainfall, and rural population variables to agricultural production in a single model. This information is vital for legislators to identify which economic or environmental factors hinder agricultural output and which support it.

## 5. Conclusion and policy recommendations

This study investigated how economic factors, which measure Domestic investment and Rural Populations, and environmental factors, which measure CO2 and rainfall, affect agricultural productivity in Somalia from 1990 to 2023; this paper used the Autoregressive Distributed Lag (ARDL) technique and cointegration analysis methods including FMOLS, DOLS, and CCR. The findings of this study offer valuable insights into the relationships between domestic investment CO2, rainfall, rural population, and agricultural output. The ARDL results of this study showed that domestic investment, carbon dioxide emissions, rainfall, and rural population significantly impact agricultural productivity in Somalia. Over the long term, increases in domestic investment and rural population growth positively affect agricultural output, underlining the importance of investing in infrastructure, human capital, and agricultural development initiatives. On the other hand, higher levels of carbon dioxide emissions negatively affect agricultural productivity, highlighting the need for policies to reduce emissions and mitigate climate change effects. Moreover, rainfall is a crucial factor positively impacting agricultural output, emphasizing the significance of water management and conservation efforts in enhancing agricultural productivity, particularly in rain-fed agricultural systems. The short-run results of ARDL revealed that $CO_2$ and domestic investments positively affect agricultural production in Somalia. This suggests that $CO_2$ emissions may temporarily increase agricultural output due to their fertilization effect on plant growth. However, rainfall negatively affects agricultural production in Somalia. This implies that the immediate disruptive impacts of excessive or insufficient rainfall conditions in Somalia may adversely affect agriculture. The cointegration results of FMOLS, DOLS, and CCR confirmed the long-run results of ARDL, which indicated that Domestic investment, rainfall, and rural population growth positively contributed to agricultural production in Somalia, while CO2 emissions hurt it. Based on the findings, several policy recommendations can be proposed to enhance agricultural productivity in Somalia. Policymakers should prioritize investment in agricultural infrastructure, technology, and human capital development to increase agricultural outputs in the long term. Initiatives to improve access to markets, information, and inputs should take precedence to promote sustainable agricultural growth and productivity. The government should implement policies and strategies to mitigate carbon dioxide emissions and address climate change impacts on agriculture, including promoting renewable energy sources and sustainable land management practices. Supporting rural development activities to harness the potential of the rural population in enhancing agricultural productivity is essential, achieved through investments in education, healthcare, and agricultural extension services. Policymakers should strengthen water management and conservation efforts to ensure the sustainable use of water resources for agriculture through irrigation schemes and rainwater harvesting techniques. Investing in research and innovation to develop climate-resilient crop varieties and sustainable farming practices is crucial, alongside collaboration with research institutions and farmers, to disseminate knowledge and adopt best practices. Implementing these recommendations can bolster Somalia's agricultural productivity, food security, and sustainable development, contributing to economic growth and prosperity while aligning with the Sustainable Development Goals.

While this study makes significant contributions, it also acknowledges certain limitations. These include the potential presence of unobserved variables that could influence agricultural productivity but were not included in our model. Another limitation is the study's focus on Somalia, which limits the generalizability of the results to other regions with different environmental and economic conditions. Thus, future studies could investigate the effect of environmental and economic factors in paned conditions.

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## About the authors

***Ali Yusuf Hassan*** contributed significantly to the research process by providing valuable research methodology and data analysis, drafting the initial manuscript, and making critical revisions.

***Mohamed Abdukadir Mohamed*** focused on developing the introduction, writing the literature review, assisting in data collection, and interpreting the findings.

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## Data availability statement

The data analyzed in the study are publicly available and sourced from reputable institutions such as the Statistical, Economic, and Social Research and Training Centre for Islamic Countries SESRIC Database, the Food and Agriculture Data FAOSTAT Database, and the World Development Indicator WDI Database. However, interested researchers may request this data from the authors for further analysis.

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