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The influence of climate change on crop production: Evidence from Somalia

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Abstract: The study examines the effect of climate change on crop production in Somalia for the period 1990 to 2022 obtained from the World Bank and FAOSTAT. Initial assessments were conducted on the data using various techniques, including the Correlation Matrix, Augmented Dickey-Fuller test, and Phillips-Perron unit root test. The findings from both the Bounds test and Johansen test demonstrate the existence of cointegration within the model. To estimate the parameter values of the regression model, three methods were employed: the Autoregressive Distributed Lagged (ARDL) model, Dynamic Ordinary Least Squares (DOLS), and Fully Modified Least Squares (FMOLS). The study's results demonstrate a positive and significant influence of foreign direct investment (FDI) on crop production. Specifically, the impact of FDI is found to be more pronounced in the long term compared to the short term. Similarly, the study finds that the harvested area and labor force have substantial positive impacts on crop production, both in the short run and long run. Based on the ARDL model results, the study finds that rainfall and temperature do not have a beneficial influence on crop production in both the short run and long run. This is becuase, Somalia is considered as one of the most susceptible countries to the effects of climate change globally. The paper advises Somalia's government to focus on developing heat-resistant crops to counter the opposing effects of temperature on crop production and ensure food security. It also requires a comprehensive agriculture funding-framework including emergency assistance.

Keywords: *Arable Land, ARDL, Climate change, Crop production, DOLS, FMOLS, Precipitation, Somalia, Temperature.*

1. Introduction

This century is being profoundly affected by climate change, and Somalia, like the rest of Africa, is especially susceptible to its consequences. The atmosphere, ocean, cryosphere, and biosphere have changed rapidly. Global rainfall patterns, temperature fluctuations, the regularity and intensity of severe weather, and climatic extremes are all being affected by human-caused climate change. This has caused significant devastation to people and nature (IPCC, 2023). Climate change and its environmental effects are happening now at a rate never seen before, making it difficult for the government and society to adjust to and deal with the changing environment. Changes in climate and the environment increasingly destabilize the systems that support the livelihoods of billions of people around the globe (UNDP, 2023).

There's no doubt that human activity has significantly impacted the warming of our planet's atmosphere, oceans, and land. Between 1901 and 2018, the average worldwide sea level witnessed a rise of 0.20 meters, ranging from 0.15 to 0.25 meters (IPCC, 2023). Between 1901 and 1971, the average pace of rising sea levels was at 1.3 [0.6 to 2.1] mm per year. This rate increased to 1.9 [0.8 to 2.9] mm annually from 1971 to 2006, and then escalated even more to 3.7 [3.2 to 4.2] mm per year from 2006 to 2018 (IPCC, 2023). It is highly probable that human intervention has been the primary factor behind these surges since at least 1971, if not earlier.

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The effect of climate change, which have been getting more sever over the past two to three decades, are having a negative impact on global food supply (FAO, 2015). Agriculture is the industry most sensitive to climate change. Climate change affects agricultural output through rainfall patterns, temperature rise, sowing and harvesting dates, water availability, evapotranspiration, and suitability of land (Janjua, et al., 2010). As stated by Shakooret et al, (2015), climate change has been a more significant danger to the socioeconomic and agricultural growth of any nation than any other factor considered. Agricultural output is negatively influenced by both temperature and precipitation (Ali, et al., 2021). Climate variability (temperature and precipitation) and climate-driven extremes such as floods, droughts, and heat stress have a detrimental effect on agricultural production in Asia (Habib-ur-Rahman, et al., 2022). Furthermore, it is anticipated that climate change would have an effect on the production of cereal crops in Sub-Saharan Africa (SSA), with significant regional variation in yield forecasts (Mereu, et al., 2015).

Moreover, climate variability can have a significant impact on agriculture resulting in elevated crop damage, reduced productivity, and heightened operational expenses. These challenges pose vast implications on the industry. Anabaraonye, et al. (2021) found that climate change reduces soil fertility and plant growth in climate-smart agricultural systems in Nigeria. Soil degradation has also been discovered to negatively affect crop production, leading to food insecurity. Moreover, Pakistan's agricultural productivity is being negatively impacted by crop diseases brought on by climate change (Abbas, 2021). The productivity of animals and agriculture are both impacted by climate variability and the frequency of extreme weather events like windstorms, droughts, and floods (Quandt & Kimathi, 2017). Farmers are less likely to participate in agriculture due to the climate change as it lowers their income and causes inequality and misery (Chandio, et al., 2020). In addition, the frequency and severity of extreme weather events like cyclones, floods, and droughts are rising due to climate change. In addition to impairing agricultural output, these occurrences upset the equilibrium of water supplies. (Baig & Amjad, 2014).

The tropical and subtropical regions especially Sub-Saharan African nations are more susceptible to the effects of rising temperatures, which can result in the destruction of crops as well as an increased need for water. It results in famines and floods, which in turn causes a country's socioeconomic standing to deteriorate (Samatar, 2023; Msowoya, et al., 2016). The amount of direct water available to crops may vary due to variations in the frequency and intensity of rainfall brought on by climate change, the severity of drought on crops, the health of livestock, the availability of forage, and the efficacy of irrigation systems (Shankar & Shikha, 2017). Furthermore, according to Adimassu and Kessler (2016), sub-Saharan Africa is subjected to a disproportionate impact of climate change as a result of its significant reliance on agriculture, which is dependent on rainfall. As a consequence, the region is unable to adequately foresee and mitigate the far-reaching implications of such catastrophes.

There is a very modest amount of land in Somalia that is used for rainfed farmland, which is estimated to be 234,000 hectares (Bremer, 2021; NCEA, 2021). The most susceptible country to Climate change's impacts and the one with the least amount of preparation is Somalia (NCEA, 2021). The effects of climate change are having a disproportionately negative impact on vulnerable communities, such as that of Somalia, which have historically contributed the least to the present climate change. Between 3.3 and 3.6 billion people reside in regions that are vulnerable to climate change (IPCC, 2023). Africa's agriculture, water, and food security are suffering from climate change. Food insecurity is caused by periodic droughts and floods affecting crop productivity. Somalia, located in a highly vulnerable region, is particularly affected by climate change.

It is estimated that about 8.3 million people across the country of Somalia would endure a crisis (IPC Phase 3) or severe acute food insecurity as a result of the effects of five consecutive seasons of inadequate rainfall (IPC, 2022), a phenomenon not observed in at least the past 40 years (FSNWG, 2022). In general, Somalia is classified as an arid to semi-arid country that receives 250 mm of rain annually. The northern maritime plains are hot and dry, with an average annual rainfall of less than 250 mm. The south and south-west receive 400 mm and 700 mm of average annual rainfall, respectively

(NEC Somalia, 2022). The production of cash crops and cereal in riverine areas has been further hampered by reduced water levels in the Shabelle and Juba Rivers, which have resulted in a string of unsuccessful cereal harvests for households in livelihood zones that are riverine and agropastoral (IPC, 2022).

Due to their reliance on agriculture, Horn of Africa countries are particularly vulnerable to climate change and suffer severe natural resource shortages, particularly water and arable land for food production (UNDP, 2023). Somalia has a population mainly living in rural areas and is situated in the Horn of Africa. The country's economy is centered around agriculture, which makes up 75% of the GDP, and this sector is also the main source of livelihood for the majority of the population employing above 45.8% (World Bank & FAO, 2018).

The availability of staple crops is being severely impacted due to a significant decline in crop yields, exceeding 40-60 percent of the long-term average, affecting both irrigated and rainfed crops (IMF, 2022). Furthermore, in the past few years, fluctuations in climate patterns have had a detrimental impact on agricultural output in various regions of the country. This has resulted in recurrent crop failures and reduced yields, as a consequence of consecutive instances of inadequate rainfall followed by destructive floods that have wreaked havoc on crops. As a result, there has been a significant decline in both crop and livestock production. Previous research demonstrates that climate change is causing a rise in temperature while also having negative impacts on rice crops, It will eventually result in lower crop quality and output. (Joyo, et al., 2018). Climate change threatens global agricultural productivity and food security (Abbas, 2021).

Ideally, comprehensive studies investigating the influence of climate change on crop production in Somalia would provide empirical evidence supported by up-to-date data and sophisticated methodologies. Such studies would not only address the unique challenges faced by Somalia's agricultural sector but also offer practical policy recommendations to mitigate the adverse effects of climate change and enhance agricultural productivity.

However, the existing literature lacks comprehensive and up-to-date data specifically focused on Somalia, leaving a significant research gap regarding the specific effects of climate change on crop production in the country. While some studies have examined the climate-crop nexus in Somalia, they often overlook critical factors such as land use, foreign direct investment, and the labor force. Furthermore, existing research primarily concentrates on other regions, neglecting Somalia's distinct agricultural landscape and challenges.

This lack of comprehensive research and policy recommendations poses significant challenges for Somalia's agricultural sector, which serves as the main source of employment and income for the majority of the rural population. Without tailored solutions addressing the influence of climate change on crop production, Somalia faces heightened risks of food insecurity, poverty, and socio-economic instability. Additionally, the absence of effective policies exacerbates the vulnerability of Somalia's agricultural sector to climate-related shocks, hindering its potential for growth and development.

This study aims to bridge the identified research gaps by conducting a thorough investigation into the influence of climate change factors on crop production in Somalia between 1990 and 2022. Utilizing data from reputable sources such as the World Bank and FAOSTAT, this research employs sophisticated econometric models and methodologies to analyze the complex interactions between climate change variables and crop production. By providing empirical data and comprehensive analysis of multiple factors such as land use, foreign direct investment, and labor force in addition to climate variables this study seeks to offer practical policy recommendations tailored to Somalia's agricultural sector, thereby contributing to enhanced agricultural productivity, food security, and socio-economic development in the face of climate change.

2. Literature Review

Over the past recent decades, climate change has had an adverse effect on crop productivity globally due to alterations in temperature, the occurrence of severe weather events, precipitation patterns, pests, and diseases. The rise in temperature results in heat stress and impacts the development of plants, while changes in precipitation can lead to water stress and crop damage. Numerous studies have utilized econometric models, the Ricardian model, crop simulations, and other methods To evaluate the influence that climate change will have on agriculture and food security. In general, the impact of climate change will be quite significant.

In Pakistan, Chandio, et al., (2020) examined CO2 emissions, rice output, planted area, average temperature, and fertilizer usage. In order to strengthen the empirical results, the paper makes use of yearly time series data spanning between 1968 to 2014. The impacts of climate change on rice production are investigated using cointegration analysis with the auto-regressive distributed lag (ARDL) bounds test. Additionally, the canonical cointegrating regression (CCR) and fully modified ordinary least squares (FMOLS) techniques are used to confirm the predicted long-run results. Empirical findings showed the cointegration of the chosen study variables, indicating long-term relationships. The study found that Pakistani rice production is favorably influenced by CO_2 emissions in both in the short and long run.

Tajudeen, et al., (2022) conduct research in Lagos, Nigeria, to determine how the effects of climate change are affecting the production of food crops such as cassava and maize. The examined weather data from 1998 to 2018 shows a little influence on cassava output but a considerable impact on maize production. Climate change reduces crop yield, soil fertility, limits soil water availability, contributes to pests spread, and increases soil erosion. Despite the negative effect of climate change on crop production, a lack of access to modern farming equipment that would reduce overreliance exacerbates the agricultural conditions in Nigeria. Access to affordable credits, creative climate change adaptation measures, and irrigation systems are needed to attract young and older farmers, according to this study.

A research that was carried out by Kumar, et al., (2021) investigated the influence that climate change, ecological variables, and carbon footprint had on the production of rice crops in India between the years 1982 and 2016. This research examined the correlation between these variables and their effects on India's rice industry. For the purpose of providing support for their study and conclusions, the writers of the research piece make use of methods such as canonical cointegration regression (CCR), autoregressive distributed lag (ARDL), and fully modified ordinary least squares (FMOLS). There is a long-term connection discovered between climatic change and India's rice cultivation. The findings reveal that both ecological and carbon footprints stimulate sustained rice production. Although rain plays a vital role in enhancing short-term agricultural productivity, it negatively affects it in the long run. Additionally, the results that are reached from the ARDL models are supported by other cointegration models, notably the FMOLS and CCR models with their respective conclusions.

Shakoor, et al., (2015) examined Pakistan's rice crop production and climate variability. By using a Vector Auto Regression (VAR) model, this study conducts an empirical analysis of the impacts of climate change on Pakistan's rice production. The climate factors' annual seasonal data ranged from 1980 to 2013. Findings revealed that higher mean maximum temperatures will reduce rice output, but higher mean minimum temperatures would be beneficial. According to Variance Decomposition, a change in the mean minimum temperature led to a 7% boost in rice yield. Simulations for the year 2030 indicated that a significant rise in rainfall and mean temperature will have a detrimental impact on rice productivity in the far future despite the fact that these factors will enhance rice yield in the short term. The study further recommended that adequate policy action is beneficial to safeguard crop production from disastrous effects.

Mwangi (2023) conducted an extensive examination of the consequences of climate change on agricultural food production. The study adopted a desk review approach that relied on secondary data, such as an analysis of existing literature from previously published studies and reports that were easily accessible through digital journals and libraries. The investigation showed that climate change has a detrimental effect on crop yields, livestock production, and viticulture by causing rising temperatures, changes in rainfall patterns and increased frequency of extreme weather occurrences. These findings repeatedly show that climate change poses a significant threat to food security and agricultural livelihoods in many countries.

Through an eclectic production model, Abbas (2021) examined the dynamic connection between yearly temperature and the main crop production such as cotton, sugar cane, mastered oil, wheat, rice, gam, bajra, barley, maize, and jowar in Pakistan from 2000 to 2019. The study found that rising temperatures had a substantial negative influence on chosen crop output in the long run but had no effect in the short term. In a similar manner, Jan, et al., (2021) utilized the second generation of panel cointegration analysis in order to investigate the influence that climate change (CO2) emission had on wheat and maize yields in the northern climatic area of Khyber Pakhtunkhwa (KP) in Pakistan between the years 1986 and 2015. Increasing the amount of precipitation has been found to have a large beneficial impact on grain output, namely maize and wheat. On the other hand, a rise in the average temperature has been found to have a minor impact over the course of various time periods.

The authors Sossou, et al., (2020) considered the effect that climate change has on the amount of cereal that is produced in Burkina Faso. Through intense analysis of time-series data collected from the World Bank website between 1991 and 2016, the study applied the ordinary least squares (OLS). The results showed that yield and cereal production are adversely affected by temperature but positively influenced by precipitation. This groundbreaking study highlights the crucial effects of climate change on cereal yield in Burkina Faso. Carbon dioxide (CO_2) emissions were found to have no significant effect on yield or crop output.

Samuel, et al. (2022) investigated the effects of climate change on crop productivity in the Nigerian agricultural sector from 1990 to 2020. During the course of this investigation, the Non-linear Autoregressive Distributed Lag (NARDL) Model was utilized. Results have shown that increased temperature has negative impact on crop yield as well decrease in rainfall. The research further recommends and urges farmers to be provided with irrigation equipment, including dams, pumps, hoses, wells, and boreholes, since doing so will assist farmers cope with water shortages brought on by climate change.

This study by (Kumar, et al., (2021)uses a balanced panel dataset covering 1971–2016 to objectively investigate the influence of climate change on production of cereals in a selection of lower-middle income nations. Climate change was measured by average yearly temperature and rainfall. Control variables including CO2 emissions, cereal-producing land, and rural population were used by the study. Unit root tests of the second generation, such as CIPS and CADF, are applied so as to determine whether or not the factors remain stationary. The models known as feasible generalized least square (FGLS) and thoroughly modified ordinary least square (FMOLS) are applied in order to fulfill the goal being sought for. An increase in temperature, as indicated by the findings of the study, leads to a reduction in the production of cereal in countries with lower-middle incomes. This is in contrast to the fact that rainfall and emissions of carbon dioxide have a positive influence on the production of cereal. The temperature's negative impacts on cereal output are anticipated to have significant repercussions for the country's overall food security.

3. Methodological Framework

This section provides a detailed account of the data source, model specifications, and estimation techniques employed to investigate the influence of Climate Change on Crop Production, with Crop Production (CP) serving as the dependent variable. The independent variables considered in this study include Foreign Direct Investment (FDI), Area Harvested (AH), Labour Force (LF), Rainfall (RF), and Annual Mean Temperature (AMT). Among these variables, the annual mean temperature and annual rainfall are utilized as proxies for climate change.

3.1. Data Description

The study's sample duration spans from 1990 to 2022, and the data is obtained from diverse international open-data repositories. The data of labour force, rainfall, and annual mean temperature have been collected from (World Bank, 2023); whereas the data of crop production, foreign direct investment, and area harvested were collected from (FAO, 2023). Table 1 provides an overview of the variables' description and summary statistics.

Table 1.
Variables description.

Acronym	Measure	Unit	Database
CP	Crop production	100 g/ha	FAOSTAT
FDI	Foreign direct investment	Million USD	FAOSTAT
AH	Area harvested	Ha	FAOSTAT
LF	Labour force	Million	WDI
RF	Rain fall	mm per year	WDI
AMT	Annual mean-temperature	Monthly Average	WDI

3.2. Bounds test/Autoregressive Distributed Lag (ARDL) Model

The autoregressive distributed lag (ARDL) bounds testing approach that was introduced by Pesaran (1997) is utilized in this particular study in order to examine the long-term cointegration relationship that exists between the explanatory factors and the dependent variables, as well as to consider the short-run dynamics. The ARDL model offers advantages over the Engle and Granger (1987) and Johansen and Juselius (1990) models. When applying the ARDL model, it is important to consider that the data can exhibit either *I(0)* or *I(1)* properties, or both combined. However, it is crucial to note that the ARDL approach becomes inappropriate if any series are integrated at a level two or above. To ensure that none of the series is integrated at the second or higher order, examining the variables' stationarity is essential.. Another benefit of utilizing the ARDL model is its suitability for small sample sizes and its ability to avoid the issue of endogeneity. As stated by Pesaran, Shin, and Smith (2001), the boundaries test is preferred over the Johansen method of cointegration.

Therefore, the PP and ADF tests to determine whether the variables are stationary, which is crucial for ensuring their stability over time. Results indicate that some variables are stationary at the level, while others are stationary at first differencing. This suggests that the variables are suitable for the ARDL model, which can handle both stationary levels.

Additionally, the Bounds test and Johansen cointegration results demonstrate whether the variables are cointegrating.. Cointegration implies a long-term relationship among the variables, which is important for analyzing their interactions and dynamics over time. The Bounds F-statistics value exceeds both the lower and upper bounds at a 99% confidence level, and the Johansen cointegration results show three cointegrated equations, further supporting the suitability of the ARDL model for the study.

3.3. Fully-modified OLS (FMOLS) Estimates

It is crucial to assess the sensitivity and robustness of the long-run parameters resulted from the ARDL model before making a final decision regarding the parameter estimates. The Fully Modified Ordinary Least Squares (FMOLS) approach, which was developed by Phillips and Hansen (1990), and the Dynamic Ordinary Least Squares (DOLS) method, which was presented by Stock and Watson (1993), are both utilized in the process of re-estimating the model. This is done in order to guarantee the accuracy of the estimates. This approach allows for a comprehensive assessment of the model's robustness. The Equation (1) for FMOLS is as follows:

$$\hat{O}FMOLS = \left(\sum_{t=1}^{t} Z_t Z_t'\right)^{-1} \left(\sum_{t-1}^{t} Z_t Z_t^{+} - T\left[\lambda_{12}^{+}\right]\right) \quad (1)$$

Where the endogeneity and serial correlation are corrected by Y_t^{+} and Y_{12}^{+} terms.

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3.4. The Dynamic OLS Estimates

The Dynamic Ordinary Least Squares (DOLS) method, developed by Saikkonen (1991) and further refined by Stock and Watson (1993), employs a parametric method to estimate a long-run relationship within a model where the variables exhibit different orders of integration but remain cointegrated (Masih & Masih, 1996). This technique allows for the estimation of a robust long-term link between the variables.. The DOLS method, as described by Kurozumi and Hayakawa (2009), not only eliminates the problem of small sample bias, but it also reduces the impact of simultaneity bias by combining both leads and lags into the method of analysis. The least squares estimates, which are unbiased and efficient even in the face of endogeneity problems, serve as the basis for the estimators employed in DOLS. The Equation (2) for DOLS is as follows:

$$y_t = a + bX_t + \sum_{i=-k}^{i=k} \emptyset \Delta X_{t+i} + \epsilon_t \quad (2)$$

In equation (2), the parameter "b" represents the long-run elasticity. The coefficients "$\emptyset s$" correspond to the leads and lags differences of the *I(1)*. According to Herzer and Nowak-Lehmann (2006), the coefficients mentioned above are regarded as nuisance parameters, and their purpose is to account for potential issues such as endogeneity, autocorrelation, and non-normal residuals. They play a crucial role in the adjustment process.

3.5. Model Specification

Aside from annual mean temperature and precipitation changes, numerous factors can impact the crop production in Somalia. These factors include area under cultivation, water availability, specific crop prices, fertilizer usage, seed quality, improved seed quality, prices of substitute and complementary goods, concentration of CO_2, and access to credit and microfinance. The model's capacity to incorporate particular explanatory variables has been hindered as a result of the absence of data for significant variables from the years 1990 to 2022. The expression of the function can be found in Equation (3), which is explained below.

$$CP = f(FDI, AH, LF, RF, AMT) \quad (3)$$

$$lnCP_t = \beta_0 + \beta_1 lnFDI_t + \beta_2 lnAH_t + \beta_3 lnLF_t + \beta_4 lnRF_t + \beta_5 lnAMT_t + \mu_t \quad (4)$$

To address heteroskedasticity and facilitate the interpretation in terms of elasticity, the variables are logarithmically transformed.

Where $lnCP$ shows the natural logarithm of crop production , $lnFDI$ indicates the natural logarithm of foreign direct investment , $lnAH$ stands for the natural logarithm area harvested , $lnLF$ represents labour force in natural logarithm, $lnRF$ denotes average rainfall in natural logarithm, $lnAMT$ represents annual mean temperature in natural logarithm, and μ indicates the error. The ARDL approach employed in this study investigates the existence of a long-run relationship, depicted in Equation (5).

$$\begin{aligned} \Delta ln\boldsymbol{CP_t} = \lambda_0 &+ \sum_{k=1}^{n} \lambda_{1k} \Delta lnCP_{t-k} + \sum_{k=1}^{n} \lambda_{2k} \Delta lnFDI_{t-k} + \sum_{k=1}^{n} \lambda_{3k} \Delta lnAH_{t-k} + \sum_{k=1}^{n} \lambda_{4k} \Delta lnLF_{t-k} \\ &+ \sum_{k=1}^{n} \lambda_{5k} \Delta lnRF_{t-k} + \sum_{k=1}^{n} \lambda_{6k} \Delta lnAMT_{t-k} + \beta_1 lnCP_{t-1} + \beta_2 lnFDI_{t-1} + \beta_3 lnAH_{t-1} \\ &+ \beta_4 lnLF_{t-1} + \beta_5 lnRF_{t-1} + \beta_6 lnAMT_{t-1} + \varepsilon_t \end{aligned} \quad (5)$$

The null hypothesis of $H_0 = \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6$ while the alternative hypothesis $H_1 \neq \beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq \beta_6$ is tested in Equation (5).

Equation (6) formulates the error correction term (ECT) for the estimated ARDL model, which captures the short-run relationship.

$$\Delta ln\boldsymbol{CP_t} = \lambda_0 + \sum_{k=1}^{n} \lambda_{1k}\Delta lnCP_{t-k} + \sum_{k=1}^{n} \lambda_{2k}\Delta lnFDI_{t-k} + \sum_{k=1}^{n} \lambda_{3k}\Delta lnAH_{t-k} + \sum_{k=1}^{n} \lambda_{4k}\Delta lnLF_{t-k} + \sum_{k=1}^{n} \lambda_{5k}\Delta lnRF_{t-k} + \sum_{k=1}^{n} \lambda_{6k}\Delta lnAMT_{t-k} + \gamma\alpha ECT_{t-1} + \varepsilon_t \tag{6}$$

Where the coefficient $\boldsymbol{\gamma}$ in the equation shows the error correction coefficient, which quantifies the speed at which the system adjusts from the short-run dynamics to the long-run equilibrium following a shock. The researcher opted to utilize EViews 9.0 econometric software for conducting the data analysis. This decision was motivated by the software's availability of the ARDL tool, which is essential for implementing the ARDL approach in the study.

4. Results and Discussion

In this section, the findings of the estimation are presented, and a connection between climate change and crop production in Somalia is established for both the short run and the long run.

4.1. Results of Unit Root Analysis

According to the information provided in Table 2, the stationarity of the variables was measured using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. Stationarity is a crucial step in estimating the model, signifying that the variable's mean and variance remain constant. If the mean and variance are not constant for a variable, it is considered to have a unit root. Consequently, various methods are applied to transform non-stationary (unit root) data into stationarity. The stationarity results presented in Table 2 demonstrate that CP, FDI, AH, LF, RF, and AMT are stationary at the level. However, RF and AMT initially exhibited a unit root, but they became stationary when differenced once. Given that the variables are shown to be stationary at both the level and the first difference, this suggests that the ARDL model can be used.

Table 2.
Results of ADF and PP unit root test of the time series of variables.

Result of ADF unit root test of the variables					Result of PP unit root test of the variables				
	I(0)		I(1)		I(0)		I(1)		
Variables	**t-stat**	**P-value**	**t-stat**	**P-value**	**t-stat**	**P-value**	**t-stat**	**P-value**	**Decision**
LnCP	-3.88	0.000	-8.82	0.000	-4.00	0.004	-14.54	0.000	I(0) & I(1)
LnAH	-3.47	0.0156	-5.95	0.000	-3.44	0.016	-14.52	0.000	I(0) & I(1)
FDI	1.67	0.9994	-5.90	0.000	1.67	0.999	5.89	0.000	I(1)
LnLF	-0.70	0.831	-4.55	0.001	1.00	0.995	-5.11	0.000	I(1)
LnRF	-3.03	0.042	-10.96	0.000	-5.09	0.000	-24.64	0.000	I(0) & I(1)
AMT	-3.66	0.009	-8.47	0.000	-3.61	0.011	25.39	0.000	I(0) & I(1)

Source: The output of the ADF unit root test of the variables in EViews 12.

Table 3 presents the descriptive statistics for various variables, including crop production (CP), area harvested (AH), foreign direct investment (FDI), labor force (LF), rainfall (RF), and annual mean temperature (AMT). Among these variables, FDI exhibits the highest mean value, followed by AMT, LF, AH, CP, and RF. Based on the Jarque-Bera statistics, the descriptive statistics demonstrate that the variables follow a normal distribution.

Table 3.
Descriptive statistics.

	LNCP	LNAH	FDI	LNLF	LNRF	AMT
Mean	12.46841	13.02628	147.0933	14.45219	5.624798	26.95242
Median	12.46959	13.02981	53.96000	14.47394	5.626901	26.92000
Maximum	12.99873	13.80283	542.3900	14.96550	5.854126	27.34000
Minimum	11.68581	12.46843	-3.510000	13.96024	5.439122	26.60000
Std. Dev.	0.352439	0.285967	187.9522	0.305530	0.096806	0.183763
Skewness	-0.251156	0.222615	0.978278	-0.044194	0.378803	0.228637
Kurtosis	2.084902	3.014742	2.489139	1.835486	3.322614	2.377230
Jarque-Bera	1.498368	0.272865	5.622500	1.875368	0.932315	0.820796
Probability	0.472752	0.872465	0.060130	0.391533	0.627408	0.663386
Observations	33	33	33	33	33	33

Source: EViews 12 output for the result of descriptive statistics.

It is crucial to look at the correlation between variables before running the regression model. The correlation matrix, displayed in Table 4, indicates that there is no significant correlation among the variables. This implies that multicollinearity, which refers to high correlations between independent variables, is not present in the estimated models.

Table 3.
Correlation matrix.

Variables	LNCP	LNAH	FDI	LNLF	LNRF	AMT
LNCP	1.000					
LNAH	0.742989	1.000				
FDI	-0.536198	-0.607544	1.000			
LNLF	-0.375830	-0.576961	0.884393	1.000		
LNRF	-0.168633	-0.159967	0.426000	0.476832	1.000	
AMT	-0.242177	-0.282202	0.529186	0.628943	0.313145	1.000

Source: EViews 12 output for the correlation matrix.

Table 4.
Results of lag order selection criteria.

Endogenous variables: LNAH LNAMT LNCP LNLF LNRF						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	148.9636	NA	6.37e-11	-9.287976	-9.056688	-9.212582
1	258.7025	176.9981	2.76e-13	-14.75500	-13.36727*	-14.30263
2	295.3324	47.26442*	1.49e-13*	-15.50532*	-12.96115	-14.67598*

The Table 5 above presents results of lag order selection, encompassing endogenous variables LNAH, LNAMT, LNCP, LNLF, and LNRF, over the sample period crossing from 1990 to 2022, totaling 31 observations. It reveals that as the lag order increases from 0 to 2, there is a corresponding improvement in model fit, as evidenced by the increase in log-likelihood values. Notably, the likelihood ratio (LR) statistic also demonstrates substantial gains in model fit with each incremental increase in lag order. Furthermore, the previous selection criteria, such as, Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SC), and Hannan-Quinn Criterion (HQ), consistently favor higher lag orders, indicating enhanced predictive performance and model fit. Specifically, lag 2 emerges as the preferred lag order across most criteria, as denoted by asterisks, suggesting that a model with a lag order of 2 is most suitable for capturing the temporal dynamics among the variables under consideration. This interpretation underscores the importance of selecting an appropriate lag order in VAR modeling to ensure robustness and accuracy in analyzing the relationships between the endogenous variables over the specified sample period.

Table 6.
Johansen cointegration test.

Series: LNAH LNAMT LNCP LNLF LNRF				
Panel A: Unrestricted cointegration rank test (Trace)				
Assumed		Trace	0.05	
No. of CE(s)	**Eigenvalue**	**Statistic**	**Critical value**	**Prob.****
None *	0.794184	114.8640	69.81889	0.0000
At most 1 *	0.681951	67.44081	47.85613	0.0003
At most 2 *	0.510459	33.07434	29.79707	0.0202
At most 3	0.284414	11.64573	15.49471	0.1747
At most 4	0.052129	1.606105	3.841465	0.2050

Note: * denotes significance at the 0.05 level
** p-values of MacKinnon-Haug-Michelis (1999).

Panel B unresticted cointegration rank test (Maximum eigenvalue)				
Assumed		**Max-eigen**	**0.05**	
CE(s) No	**Eigenvalue**	**Statistic**	**Critical Value**	**Prob.****
None *	0.794184	47.42316	33.87687	0.0007
At most 1 *	0.681951	34.36646	27.58434	0.0058
At most 2 *	0.510459	21.42862	21.13162	0.0454
At most 3	0.284414	10.03962	14.26460	0.2093
At most 4	0.052129	1.606105	3.841465	0.2050

Note: * denotes significance at the 0.05 level
** p-values of of MacKinnon-Haug-Michelis (1999)
Source: Results of EViews 12 of Johansen test (Cointegration of the variables)

Table 6 argued that there are cointegration relationships among the series LNAH, LNAMT, LNCP, LNLF, and LNRF. Both the Trace test and the Maximum Eigenvalue test argued the presence of cointegration at the 0.05 significance level. Specifically, the null hypothesis of no cointegration is rejected, demonstrating the presence of long-term equilibrium associations among the variables. These findings are important for understanding the underlying dynamics and relationships among the series, which can be valuable for forecasting and economic analysis.

4.2. ARDL Model Estimation Outcomes: The Long-Run findings

According to the results, the Bounds test proved the existence of cointegration, which stands for a long-term relationship. In Table 7, the Bounds F-statistics value of 4.051 exceeds both the lower limit (2.62) and the upper limit (3.79) at a 99% confidence level. These results imply the presence of a long-term relationship between crop production and the chosen independent variables in the study conducted in Somalia from 1990 to 2022. Moreover, the research investigates the long-term and short-term relationships between crop production and the variables of area harvested, foreign direct investment, labor force, rainfall, and annual mean temperature. The outcomes of the long-term and short-term elasticities are reported in Table 8 and the respective Table 9, respectively.

Table 5.
ARDL bounds testing results.

F-bounds test		Relationship at all levels		
Test statistic	**Value**	**Significance (%)**	**Lower bounds**	**Upper bounds**
F-statistic	4.051153[1]	10%	2.26	3.35
K	5	5%	2.62	3.79
		2.5%	2.96	4.18
		1%	3.41	4.68

Note: (s)" Superscript "1" indicates the significance level at 5%.
Source: findings of EViews 12 of bound test (Cointegration of the variables).

Table 8 reports the estimated parameters of the long-run model, which provide the findings for the long-term results. Table 8 reveals that the variables of foreign direct investment (FDI) and labor force (LF) exhibit statistical significance in the long run. On the other hand, it has been discovered that the variables of areas harvested (AH), annual mean temperature (AMT), and rainfall (RF) do not have any statistical significance throughout the long run period. The findings suggest that foreign direct investment and the size of the labor force have a meaningful impact on crop production over an extended period, while factors such as rainfall and annual mean temperature have notable detrimental impact on crop production in Somalia. Furthermore, the long-term effect of annual mean temperature change is also observed to have a significant negative influence on crop production. These findings argued that the increasing annual mean temperature is adversely affecting the productivity of crops in the long run, potentially causing disruptions in crop production performance. The statistical insignificance for the rainfall variable in the long run may be credited with the occurrence of consecutive rainfall failures in Somalia from 2017 to 2022. This means that, in the long run, the negative consequences of the rainfall failure probably outweighed the total impact of rainfall on crop productivity.

Therefore, as the annual mean temperature steadily increased throughout the study period (1990 to 2022), it became apparent that these factors had the potential to disrupt the production of particular agricultural crops and compromise food security conditions. This was due to the fact that deforestation and periodic droughts were also common during this time period.

Table 6.
ARDL long-run model results.

Dependent variable: LNCP				
Variable	**Coefficient**	**Std. error**	**t-statistic**	**Prob.**
LNAH	0.593346	0.344665	1.721515	0.0980
FDI	-0.001702	0.000698	-2.438705	0.0225
LNLF	1.116404	0.504509	2.212853	0.0367
LNRF	-0.597699	0.663440	-0.900909	0.3766
LNAMT	-11.683085	13.188773	-0.885836	0.3845
C	30.692096	39.636125	0.774347	0.4463
$R^2 = 0.797572$	Adj $R^2 = 0.783612$			
F-Statistic = 57.13052	Prob (F-statistic = 0.000000			
Durbin – Watson stat = 1.952650				

Source: EViews 12 outcomes for the long run model.

4.3. Results of ARDL Short-Run Estimation

Table 9 presents the outcomes of analyzing the short-term dynamics of how climate change affects crop production in Somalia. The analysis revealed that the majority of the variables exhibited their a priori signs, except for the area harvested variable. While the area harvested variable was statistically insignificant with a positive coefficient in the long run, it was found to have a positive impact on crop production in the short run. According to the analysis, a one-hectare increase in the area harvested (AH) is associated with approximately a US $0.92 million increase in the value added to crop production in Somalia. However, it was observed that the increase in foreign direct investment (FDI) had a statistically significant with negative coefficient. This could possibly be attributed to inefficiencies in utilizing the allocated funds for the development of the crop production sector. Moreover, a significant number of farmers continue to rely on traditional farming methods, which poses challenges in their adoption of improved crop varieties and modernized farming equipment.

In addition, the data suggest that the employment of a single person in the sector of crop production will result in an increase of around 0.772 percent in the amount of crops produced in Somalia. Furthermore, crop productivity is negatively impacted by a one-year rainfall lag as well as by the first temperature lag. This can be attributed to the occurrence of rainfall failures and the persistent increase in temperature, which have detrimental effects on crop production.

The study examined the goodness of fit of the entire model and found that the R-squared (R^2) value, which stands at 0.79, suggests that approximately 79% of the variation in crop production can be explained by the variables comprised in the model. Additionally, the Durbin-Watson statistic yielded a value of 1.95, indicating a potential presence of autocorrelation. The results of the serial correlation test, on the other hand, demonstrated that the model does not exhibit serial correlation, which is an essential assumption in this test. As an additional point of interest, the fact that the probability value of the F-statistic is 0.0000 indicates that the model is both robust and suitable for this research.

Overall, the regression is statistically significant, signifying its relevance in explaining the relationships between the selected explanatory variables and crop production.

Finally, the study found that the error correction term (ECM), which gauges how quickly the short-run model adjusts towards long-run equilibrium, was both negative (-0.69) and statistically significant. This aligns with theoretical expectations. In summary, the findings show that, on a quarterly basis, about 69% of the short-term deviations from long-term equilibrium are corrected. This suggests that the model exhibits a mechanism that brings the system back to its long-run equilibrium over time.

Table 7.
Findings of short - run estimation.

Dependent variable: LNCP				
Variable	**Coefficient**	**Std. error**	**t-statistic**	**Prob.**
D(LNAH)	0.921354	0.168591	5.465016	0.0000
D(FDI)	-0.001177	0.000494	-2.383162	0.0254
D(LNLF)	0.772358	0.319968	2.413863	0.0238
D(LNRF)	-0.413504	0.448862	-0.921227	0.3661
D(LNAMT)	-8.082664	8.117468	-0.995712	0.3293
CointEq(-1)	-0.691826	0.182360	-3.793742	0.0009
R-squared	0.797572	Mean dependent var		-0.020711
Adjusted R-squared	0.783612	S.D. dependent var		0.411870
S.E. of regression	0.191592	Akaike info criterion		-0.377838
Sum squared resid	1.064517	Schwarz criterion		-0.240425
Log likelihood	9.045405	Hannan-Quinn criter.		-0.332289
F-statistic	57.13052	Durbin-Watson stat		1.952650
Prob(F-statistic)	0.000000			
* p-value incompatible with t-Bounds distribution.				

Source: EViews 12 output for the short run model.

4.4. Results of FMOLS and DOLS

The outcomes of the fully modified OLS and dynamic OLS models are presented in Table 10 and Table 11, respectively. Both models reveal significant positive associations between the variables of foreign direct investment (FDI), and labor force (LF) with crop production in the studied period (1990 to 2022). On the other hand, the variables of rainfall (RF) and annual mean temperature (AMT) continue to be statistically insignificant. This is most likely because of the influence of climatic factors such as the failure of rainfall and the ongoing rise in temperature. Table 12 presents a comprehensive description of the findings that were achieved through the utilization of these three methodologies.

Table 10.
Result of fully modified OLS.

Dependent variable: LNCP				
Variable	**Coefficient**	**Std. error**	**t-statistic**	**Prob.**
LNAH	0.913071	0.211238	4.322473	0.0002
FDI	-0.001158	0.000562	-2.059956	0.0495
LNLF	0.809437	0.389379	2.078790	0.0476
LNRF	-0.352339	0.562871	-0.625968	0.5368
LNAMT	-2.787909	8.911449	-0.312846	0.7569
C	0.207890	27.49393	0.007561	0.9940
R-squared	0.659653	Mean dependent var		12.45960
Adjusted R-squared	0.594201	S.D. dependent var		0.354368
S.E. of regression	0.225741	Sum squared resid		1.324929
Long-run variance	0.069880			

Source: EViews 12 result of FMOLS.

Table 11.
Result of dynamic ordinary least squares.

Dependent variable: LNCP				
Variable	**Coefficient**	**Std. error**	**t-statistic**	**Prob.**
LNAH	-1.429990	0.774274	-1.846878	0.0978
FDI	-0.004425	0.001061	-4.170749	0.0024
LNLF	2.267107	0.715584	3.168192	0.0114
LNRF	4.482256	2.318347	1.933384	0.0852
LNAMT	-41.32273	24.98594	-1.653839	0.1325
C	109.4399	74.37672	1.471427	0.1753
R-squared	0.861351	Mean dependent var		12.47227
Adjusted R-squared	0.553243	S.D. dependent var		0.359577
S.E. of regression	0.240341	Sum squared resid		0.519873
Long-run variance	0.029817			

Source: EViews 12 result of DOLS.

Table 8.
Summary results of long-run coefficients and error correction term (ECM).

Variable	ARDL	FMOLS	DOLS
LNAH	0.593346 [1.721515]	0.913071 [4.322473]	-1.429990 [-1.846878]
FDI	-0.001702 [-2.438705]	-0.001158 [-2.059956]	-0.004425 [-4.170749]
LNLF	1.116404 [2.212853]	0.809437 [2.078790]	2.267107 [3.168192]
LNRF	-0.597699	-0.352339	4.482256

Variable	ARDL	FMOLS	DOLS
	[-0.900909]	[-0.625968]	[1.933384]
LNAMT	-11.683085 [-0.885836]	-2.787909 [-0.312846]	-41.32273 [1.653839]
ECM(-1)	-0.691826 [-3.793742]		
C	30.692096	0.207890	109.4399
R^2	0.797572	0.659653	0.861351

Source: EViews 12 outputs of ECM.

4.5. Post – Estimation Tests

4.5.1. Normality Test

The normality test is a crucial step in determining the distribution of the dataset used in the model. Figure 1 provides evidence regarding the null hypothesis that the variables satisfy a normal distribution, as indicated by the Jarque-Bera test. The probability value associated with the test is 0.88 which is greater than 0.05, suggesting that the data is normally distributed. This implies that the variables can be reasonably assumed to have a normal distribution in the model.

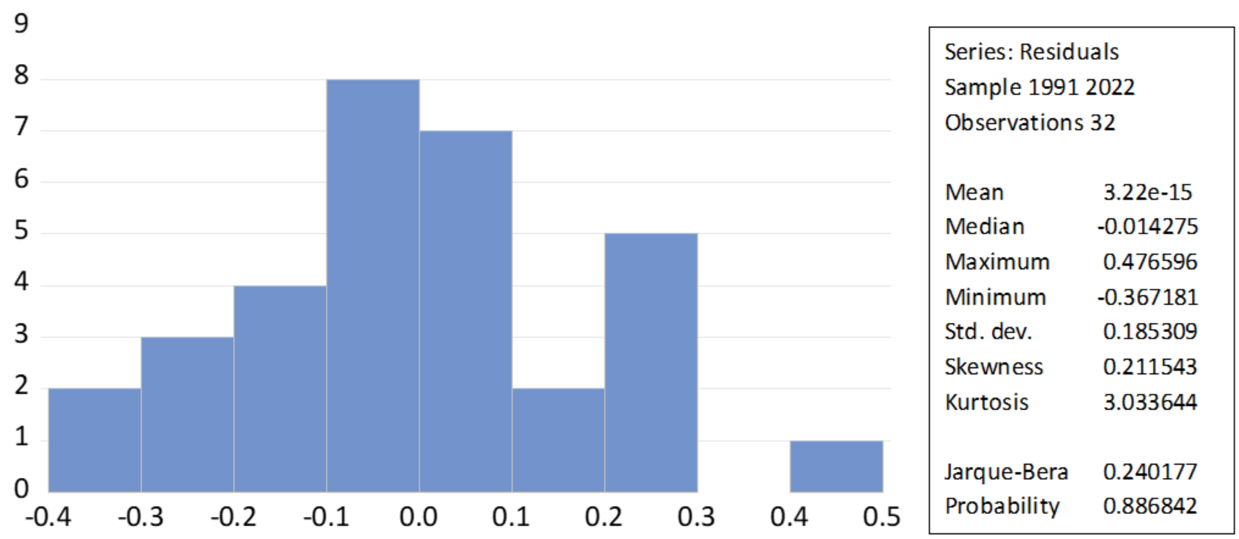

Figure 1.
Graph of normal distribution for model.

4.5.2. Serial Correlation LM Test of the ARDL Model

To examine the existence of serial correlation in the short-run ADRL model, we conducted the Breusch-Godfrey serial correlation LM test. The results, as shown in Table 13, indicate that the probability chi-square value is 0.9380, which is greater than 0.05 at a 5% level of significance. Therefore, we can conclude that there is no evidence of serial correlation in the residuals of our model. This suggests that the residuals are not systematically related to each other, supporting the assumption of no serial correlation in our analysis.

Table 13.
Result of serial correlation LM test.

Breusch-Godfrey serial correlation LM Test:			
F-statistic	0.044158	Prob. F(2,22)	0.9569

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Obs*R-squared	0.127946	Prob. chi-square(2)	0.9380

Source: EViews 12 output for the result of serial correlation.

4.6. Heteroscedasticity Test

Various diagnostic tests were employed to assess the suitability of the ARDL model. The outcomes presented in Table 14 indicate the absence of heteroskedasticity and serial correlation in the estimation. Furthermore, Figure 1, which illustrates the results of the normality tests, verifies that the data follows a normal distribution. Additionally, the stability of the coefficients in the ARDL model was confirmed through the CUSUM Plot and CUSUM Square Plot test (Figure 2 and Figure 3).

Table 9.
Analyzing heteroscedasticity.

Breusch-Pagan-Godfrey test			
F-statistic	3.627435	Prob. F(7,24)	0.0083
Obs.*R-squared	16.45094	Prob. Chi-Square(7)	0.0213
Scaled explained SS	9.409317	Prob. Chi-Square(7)	0.2246

Source: Results of EViews 12 for Heteroskedasticity.

4.7. Stability Diagnostic Test

The stability of the short-run model was assessed using the CUSUM test and CUSUM of squares test. These tests aim to determine whether the model remains stable over time. In Figure 2 and Figure 3, which depict the CUSUM Plot and CUSUM Square Plot respectively, the blue solid lines are observed to fall within the boundaries of the dotted red lines. This indicates that the model is dynamically stable, as there is no significant deviation from stability.

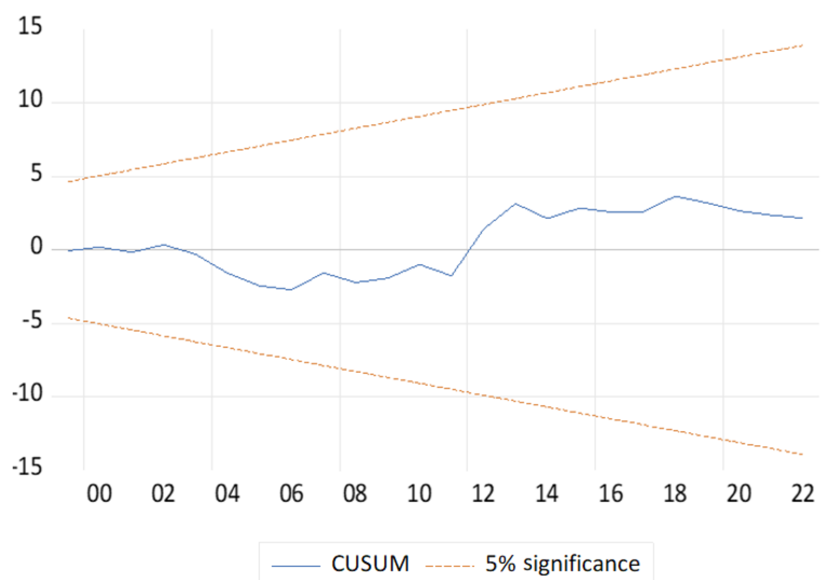

Figure 2.
CUSUM.

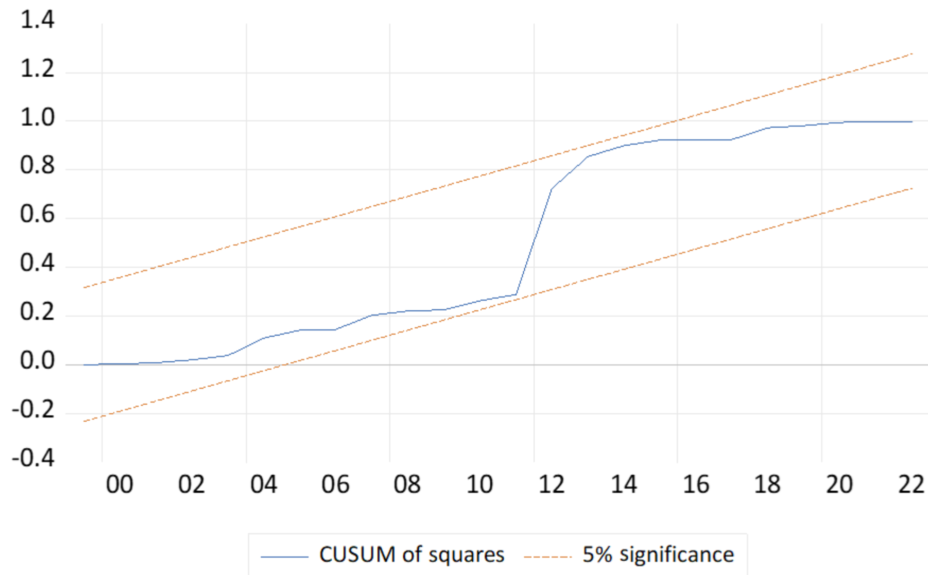

Figure 3.
CUSUM square plot.

4.8. Ramsey Reset Test

The specification test is conducted to determine if the estimated model is correctly specified. It utilizes the F-statistic, with the null hypothesis being that the model is correctly specified. If the probability value associated with the F-statistic is less than 0.05, the null hypothesis is rejected. Conversely, if the probability value is greater than 0.05, the null hypothesis is not rejected. In Table 15, the probability value of the F-statistic is found to be greater than 0.05, indicating that the research hypothesis is rejected at the 0.05 significance level. This implies that the estimated model is appropriately specified.

Table 10.
Ramsey RESET test.

	Value	df	Probability
t-statistic	1.482085	23	0.1519
F-statistic	2.196576	(1, 23)	0.1519
Likelihood ratio	2.918844	1	0.0876

Source: EViews 12 results of Ramsey RESET.

4.9. Discussions

The studies by Chandio et al. (2020) and Kumar et al. (2021) both show that CO2 emissions have a positive effect on rice production in Pakistan and India, respectively. They also highlight the negative effect of rainfall on rice production. These findings suggest a positive link between foreign direct investment (FDI) and crop production in Somalia. Additionally, rainfall does not seem to have a significant impact on crop production in Somalia according to the statistical results, which aligns with these studies.

Similarly, Jan et al. (2021) and Sossou et al. (2020) find that increased precipitation leads to higher grain output. Sossou et al. (2020) also note that while temperature negatively affects cereal yield, precipitation has a positive influence. These findings support the study result that the labor force positively affects crop production in Somalia, as indicated in the statistical results.

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Tajudeen et al. (2022) say that climate change harms maize production in Nigeria. They also say it's important to use modern farming tools and adapt, but these ideas aren't shown directly in the Somalia results.

Samuel et al. (2022) find that higher temperatures and less rainfall hurt crop yields in Nigeria. But the results in Somalia don't show rainfall as important, and the result show that foreign investment has adverse effect on crop production in the short term.

The study makes a significant contribution by synthesizing findings from various research endeavors conducted in regions such as Pakistan, India, Nigeria, and Somalia, to shed light on the intricate relationship between environmental factors, foreign investment, and crop production. By drawing parallels between studies by Chandio et al. (2020), Kumar et al. (2021), Jan et al. (2021), Sossou et al. (2020), Tajudeen et al. (2022), and Samuel et al. (2022), the research elucidates several key insights.

Firstly, it underscores the positive impact of CO_2 emissions on rice production in Pakistan and India, reinforcing the notion that environmental factors play a pivotal role in agricultural outcomes. Moreover, the acknowledgment of the adverse effect of rainfall on rice production in these regions underscores the multifaceted nature of environmental influences on crop yield.

Secondly, the study highlights the importance of foreign direct investment (FDI) in shaping crop production dynamics, particularly in Somalia. Despite contrasting findings regarding the significance of rainfall in Somalia compared to other regions, the research suggests a positive link between FDI and crop production, emphasizing the need for further exploration into the mechanisms underlying this relationship.

Furthermore, the study aligns with the findings of Jan et al. (2021) and Sossou et al. (2020), emphasizing the positive correlation between precipitation and grain output. This underscores the critical role of environmental factors, such as rainfall, in shaping agricultural productivity. Additionally, the study supports the notion that the labor force positively influences crop production in Somalia, further underscoring the multifaceted nature of agricultural dynamics.

However, the research also acknowledges discrepancies in findings, such as those highlighted by Tajudeen et al. (2022) and Samuel et al. (2022), regarding the opposing effects of climate change on maize production in Nigeria. While these findings provide valuable insights into regional variations in agricultural vulnerabilities, they also emphasize the need for nuanced approaches to agricultural adaptation and modernization, which may not directly translate to the context of Somalia.

In essence, the study contributes to the existing body of knowledge by synthesizing disparate findings and offering insights into the complex interplay between environmental factors, foreign investment, and crop production dynamics, thereby providing a valuable foundation for further research and policy formulation in agricultural development contexts.

5. Conclusion

This paper investigates the impact of climate change on crop production in Somalia by using annual time series data from 1990 to 2022. The nature of long-term and short-term relationships is examined using various statistical techniques, including the Augmented Dickey-Fuller test, Phillips-Perron unit root test, ARDL, FMOLS, and DOLS. Annual mean temperature and rainfall have been employed as measure for assessing climate change. The results of the study indicate a significant influence of climate change on crop production. Specifically, the study finds that increasing **temperatures** and decreasing **rainfall** have a detrimental effect on crop production in Somalia. Further, the findings indicate that rainfall has a negative impact on crop production in Somalia. This can be attributed to the varying levels of rainfall received by farms across different regions of the country. In recent years, certain areas in northern, eastern, and central Somalia experienced reduced rainfall amounts. On the other hand, certain regions experienced excessive rainfall, resulting in flash flooding and floods that submerged crops. This led to significant crop losses, particularly in regions traversed by the Jubba and Shabelle rivers.

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Consequently, it is crucial for farmers and the government to implement improved risk management strategies to effectively address climate-related scenarios in these areas.

The study discovered that the area harvested has a crucial influence on the increase in crop production. A surge in the cultivated land area leads to an augmentation in crop production. Similarly, foreign direct investment, area harvested, and the labor force have a significant and positive effect on crop production, both in the short run and the long run. The long-run findings of the ARDL model are supported by the FMOLS and DOLS models. The findings of the study would assist policymakers in directing their attention towards addressing the adverse impacts of temperature and enhancing the adaptive capacity of farmers to promote increased crop production in Somalia. Given the negative impact of temperature on crop production, it is imperative to conduct research and development aimed at cultivating heat-resistant crop varieties. This approach is crucial to ensure food security in the face of changing climatic conditions.

5.1. Policy Implications

Based on the analysis presented by the study, several policy implications can be drawn to address the challenges and capitalize on the opportunities identified in the study regarding the impact of climate change on crop production in Somalia:

1. Given the significant positive impact of foreign direct investment (FDI) and labor force (LF) on crop production, policies should focus on attracting and facilitating investments in agricultural technology, mechanization, and infrastructure. This can enhance productivity, efficiency, and resilience to climate-related challenges.
2. As traditional farming methods still prevail and hinder the adoption of improved practices, there is a need for comprehensive capacity-building programs targeting farmers. These programs should promote the adoption of modern techniques, crop varieties resilient to climate change, and sustainable land management practices.
3. Recognizing the adverse effects of increasing annual mean temperature and rainfall failures on crop production, policymakers should prioritize climate resilience strategies. This may include the development of drought-resistant crops, water management systems, and soil conservation measures to mitigate the impact of climate change on agricultural productivity.
4. Given the vulnerability of crop production to climate variability, diversification of crops should be encouraged to spread risk. Additionally, the establishment of crop insurance schemes can provide financial protection to farmers against crop losses resulting from extreme weather events.
5. Enhancing the capacity for accurate data collection and monitoring of climate and agricultural indicators is crucial for informed decision-making and policy formulation. Investing in meteorological infrastructure and remote sensing technologies can improve early warning systems and facilitate adaptive responses to changing climate conditions.
6. Addressing the complex challenges posed by climate change requires coordinated efforts across multiple sectors and stakeholders. Inter-ministerial collaboration, engagement with the private sector, civil society, and international partners is essential to develop holistic and effective policies for sustainable agricultural development and climate resilience.
7. Given the dynamic nature of climate change, policies should be adaptive and incorporate long-term planning horizons. Flexible governance structures that allow for iterative policy adjustments based on evolving scientific evidence and stakeholder feedback can enhance the resilience of agricultural systems to future climate uncertainties.

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