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Autoregressive Distributed Lag Modeling of Climate and Non-climatic Determinants Affecting Cereal Production: Empirical Evidence from Somalia

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ABSTRACT

This study investigates the impact of climate and non-climate factors on cereal production (CP) in Somalia from 1990 to 2019. The study used the autoregressive distributed lag (ARDL) modeling approach to analyze the effect of Carbon dioxide, temperature, rainfall, land under CP, and rural population on CP. The study employed the ARDL model to determine the long-run and short-run effects of the variables. The results indicate that all variables negatively impacted CP, except for land under CP, which had a positive effect on CP in both the short and long run. These findings suggest that policymakers should prioritize investment in land management practices to increase CP in Somalia. The study's results have important implications for stakeholders in the agricultural sector, highlighting the need for sustainable land use policies and climate change adaptation measures to ensure the country's food security.

Keywords: Climate Factors, Non-climatic Factors, Autoregressive Distributed Lag, Somalia
JEL Classifications: Q54, Q56

1. INTRODUCTION

Agriculture is among the most delicate and susceptible industries to climate change (Kotir, 2011). It is essential for the economic growth of any country, particularly developing countries like Somalia. It is a significant economic activity in Somalia not only in terms of supplying the country's people with food (around 50% of its grain needs are fulfilled domestically) but also in terms of creating money through crop sales and employment opportunities in the agricultural sector. In nations where agriculture is crucial to sustaining livelihood and food security, this weather variability poses a serious threat to sustainability. The changing climate impacts the lives of people, who utilize 70% of the world's water supplies and inhabit around 40% of the land. (Kumar et al., 2021). (FAO, 2013) reported, "Due to the violence in the nation, a long-lasting, complicated emergency has developed, eroding livelihoods and increasing vulnerability to food insecurity." Malnutrition and hunger are two of the main causes of misery for sizable portions of the population in the middle of one of the biggest humanitarian crises in history. However, due to occasional violence, floods, droughts, outbreak of diseases, and extremely not enough basic services and humanitarian space, a segment of Somali households are finding it more difficult to sustain a food-secure and well-fed home (Kenya, 2013).

The word "climate" refers to how variations in temperature (TEM), precipitation, and humidity serve as indicators of the state of the environment worldwide (Chandio et al., 2022). The most significant climate factor is Carbon dioxide (CO_2), which raises greenhouse gases, which warm the globe (Abdi Ali et al., 2022).

However, climate change improves the performance of the agriculture sector in wealthy countries, where it has a favorable effect on production, but it has a negative effect in developing countries, including greater crop losses, low productivity, and high production and operating

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expenses. In developing countries, agriculture continues to be the main source of income. Eighty percent of the people in East Africa make their living from agriculture, which accounts for 40% of the region's GDP. This place is among the poorest in the world, and a sizable section of the populace struggles with a lack of food (Rehman et al., 2021).

Several strategies have been used to raise agricultural output, including the advancement of technology, increased use of fertilizers, better seeds, and the use of additional cultivable land. These factors have increased productivity but also brought about significant climatic changes that have a big impact on the environment and farm production. Investigating the effects of climatic and non-climatic elements is therefore crucial for emerging countries like Somalia. increased productivity but also brought about significant climatic changes that have a significant impact on environmental factors and agriculture production (Chandio et al., 2022).

Farmers' incomes diminish as a result, increasing poverty and inequality and decreasing their desire to actively engage in agriculture (Alam, 2012). Through the variation in TEM and fluctuation in rainfall (RF), climate change had a direct impact on agricultural productivity in developing counties. Somalia has rich soil and cultivable land that has trusted RF. The majority of Somalia's regions are also suitable for agriculture (Mohamud Hussein and Abdi Ali, 2022).

The impact of climate and non-climatic factors on agricultural output is an academics' top priority. Human activities, such as growing urbanization, land use, production, and consumption patterns in the nation, are the main cause of climate change. The progressive rise in TEM is a result of a rising level of carbon emissions in the atmosphere, primarily brought on by industrialized nations' high levels of production. Although, developing nations that are located in tropical regions and primarily rely on agriculture are more likely to experience climate change, variations in RF, and frequent floods and droughts. Tropical and subtropical areas are particularly susceptible because of the higher TEMs that cause crop damage and increase the need for water (Baig et al., 2020).

In Africa, reliance on rain-fed agriculture, rural populations (RPs) are more vulnerable to climate change. There is growing evidence connecting climate change to both major and minor threats to natural systems, which puts environmental, social, and economic progress at risk. Climate change consequences are predicted to impede economic growth, making it very difficult to decrease poverty and extend current poverty traps (Ajuang Ogallo et al., 2018).

In Somalia, floods and droughts have been more frequent and intense, with particularly bad droughts in 2007-2008, 2011-2012, and 2015-2016. The UN estimates that between November 2016 and October 2017, the drought in Somalia caused 943,000 people to be internally displaced. This shows that Somalia's population is still displacing due to the climate. Large populations in Somalia have been more severely impacted by water stress due to their reliance on the availability of water and pasture for their livelihoods. Ninety four percent of Somalia's nomadic populations live in poverty. Vast coastlines in Somalia provide fishing jobs, but these livelihoods are threatened by unique marine processes like the region's ocean currents and tropical cyclones (Ajuang Ogallo et al., 2018). The average annual daytime TEM in Somalia is 27°C, and the country primarily experiences an arid to the semi-arid environment.

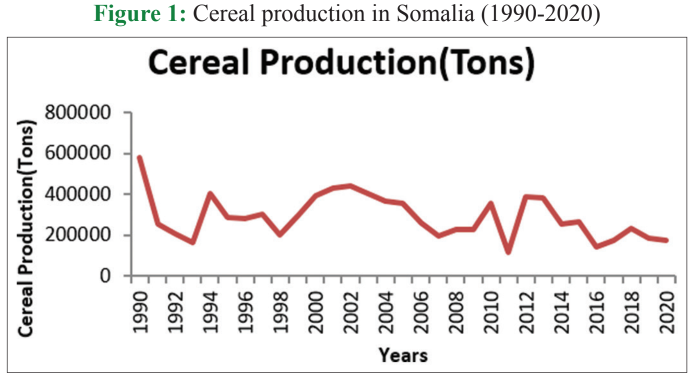
Of all the African countries, Somalia has one of the largest yearly changes in RF, and it is this unpredictability that has the most impact on the pastoral and agro-pastoral agricultural systems. The distribution of RF is bimodal. The rainy seasons are the Gu and Deyr, with the Gu seeing the heaviest precipitation (October to November). Jilal (December to March) and Hagaa are the dry seasons (July to September). On the south coast, potential evapotranspiration varies from 1500 mm to 2900 mm annually. The country experiences a small drought every three to 4 years (Kenya, 2013).

All-inclusive, cereal production (CP) in Somalia seemed to be a fluctuating pattern throughout time brought on by, among other things, droughts, civil war, and climate change. Figure 1 illustrated that the production of cereal makes trending volatility from 1990 (580,925 metric tons) to 1993 (164,925 metric tons) by declining production of cereal due to the civil war broke in 1991. The production started dramatically decreasing from 1994 (40,525 metric tons) to 1995 (284,920 metric tons). CP was quite volatile between 1996 (282,030 metric tons) and 1997 (305,334 metric tons) and also the remaining years. Though Somalia's production of cereal varied a lot in recent years, it tended to decrease and sometimes increase from the 1990 to 2020 period ending at 177,226 metric tons in 2020. A typical farm in Somalia is between 2 and 4 hectares (FAO, 2014).

Considering the previous context, the primary purpose of this research is to find out the effect of climate and climatic factors on CP in the case of Somalia. First, this literature is the first which addresses both the impact of climate and Non-climatic elements on CP in Somalia. Although, other studies contribute to the body of literature already in existence on climate change and other agricultural sectors in Somalia, including: (Warsame et al., 2022; Warsame et al., 2022). Second, the study filled a gap by considering both climatic factors (CO_2, RF, and TEM) and non-climatic factors (Land under CP, Agricultural Labor Force, and Foreign Direct Investment) which affect CP in Somalia. Third, the paper uses the autoregressive distributed lag (ARDL) technique to find out the reliable short-run and long-run impact of climate and Non-climatic factors on CP in Somalia.

The remainder of the paper is structured as follows: Section two presents the overview of the literature, and Section 3 outlines

Figure 1: Cereal production in Somalia (1990-2020)



Data Source: World Bank (2020)

the methodology. Section 4 decides on empirical results and their discussion, and Section 5 provides conclusions and policy recommendations.

2. LITERATURE REVIEW

Many studies on the critical issue of climate change and its effects on the productivity and development of world agriculture have been done in recent years. To be mindful of climate and non-climatic effects on CP (Chandio et al., 2022) investigated the impact of climatic and non-climate factors on the production of cereal in India between 1965 and 2015 from the world bank indicators. The study used three dependent variables, such as agricultural value-added, CP, and cereal yield. While the study used independent variables including CO_2, TEM, RF, energy consumption, land under CP, financial development, gross capital formation, and RP which is a stand-in for the agricultural labor force.

The study implemented (ARDL) bounds testing approach. The research indicated that climatic factors including CO_2 and TEM negatively affect agricultural output, while RF positively impacts it. Similar to how non-climatic elements like energy use, financial progress, and labor force have a favorable long-term impact on agricultural production. The anticipated long-run results further reveal that CO_2 and RF positively affect both CP and yield, whereas TEM adversely affects them. To combat the negative effects of climate change on agriculture and its production of grains, the research recommended that decision-makers and governmental bodies create extensive adaptation plans and mitigation strategies.

(Warsame et al., 2022) studied the impact of climate change and political instability on the production of sorghum in Somalia from 1980 to 2017. The study utilized sorghum production as a response variable, and political instability, land under the production of sorghum, agricultural labor force, RF, and TEM are independent variables. The data were taken from the World Bank and FAO by applying Johansen co-integration technique. The empirical finding shows that average TEMs, political unpredictability, and agricultural labor considerably reduce sorghum production in Somalia over time, whereas RF, even if it is small, and sorghum producing area increase it. To establish a stable environment, the paper advises policymakers to implement policies designed to resolve conflicts. It also suggests that land under cultivation be planted with a variety of crops to reduce the volatility that is brought to accelerate the shift from a low-productivity to a high-productivity economy caused by climatic and biological changes.

Moreover, other literature studied climate factors affecting agricultural sectors including (Chandio et al., 2022) who studied the effect of climate change on CP in Bangladesh. This study aims to examine the impacts of climate change, measured RF, TEM, and (CO_2) on CP in Bangladesh by using the annual dataset from 1988 to 2014, with the incorporation of land under CP, financial development, energy consumption, and RP as important determinants of CP. The long-term and short-term co-integration and the causality directions, respectively, were validated in this work using the (ARDL) model and several econometric techniques. The outcomes of the limits testing approach confirmed the persistent long-term relationships between the underlying variables. Yet, both in the short and long terms, CO_2 significantly worsens CP. Findings also indicated that TEM had a short-term negative impact on CP. CP in both circumstances is significantly influenced favorably by many other factors, including cereal cropped Area, financial development, and energy consumption. The one-way relationship between CP and TEM demonstrates that TEM has an impact on CP. The other factors are likewise validly and significantly related to one another causally. The recommendation to policymakers to adopt better cereal crop types, boost cereal cropped areas, and familiarize themselves with agricultural credits through formal institutions on lax conditions and low-interest rates should lessen the CP's susceptibility to climatic shocks.

3. DATA AND METHODODLGY

3.1. Data Description

To reach the goal of the study, we utilized annual time series data from the World Bank from 1990 to 2019. The study's independent variables included land, CO_2, RF, TEM, land usage, and RP, which was used as a stand-in for the agricultural labor force as a percentage of the overall population. The dependent variable for cereal output was the study's dependent variable. Afterward, to reduce heteroskedasticity, each variable was turned into a natural logarithm. Table 1 provides data descriptions and sources for the variables used in this investigation.

3.2. Econometric Modelling and Specification

Presentation of the series' descriptive statistics serves as the analysis's first stage (mean, median, minimum and maximum values, skewness, kurtosis, standard deviation, as well as the Bera-Jacque normality test, and pairwise correlation). After conducting summary statistics, we will do a trend analysis of the variable, and then a unit root analysis. It informs about the degree of integration of each variable.

We applied the ARDL approach created by Pesaran et al. (2001) to accomplish the study's goal. It performs better than earlier co-integration methods in many areas. First, unlike earlier approaches that required huge overlapping time-series data, the ARDL approach is applicable for small sample sizes. Second, independently of the variables' integration order I (0), I (1), or a hybrid of both, it can estimate the variables' long- and short-run

Table 1: Variable description and source

Variable	Code	Measurement
Nonclimatic		
Cereal production	CP	Metric tonns
Land under cereal production	LD	Hectares
Rural population	RP	Percentage of the total population
Climatic		
Carbon dioxide	CO_2	Million tonns
Rainfall	RF	Average annual precipitation (mm)
Temperature	TEM	Average annual temperature in (°C)

cointegration. Third, unlike the earlier methods, it simultaneously regresses long-run and short-run co-integration. Additionally, it considers the asymmetric behavior of bias-corrected bootstrap method coefficients and conditional error correction coefficients, which can be expected to yield reliable statistical inferences on the long-term co-integration of sampled variables. To satisfy the bounds test the assumption of the ARDL models, each variable must be I (0) or I (1).

When modeling the impact of climate change on agricultural production. Most of the researchers took into account climate factors such as RF, TEM, and CO_2. In the case of Somalia, this study investigates the short-term and long-term impacts of climatic elements such as CO_2, TEMs, and RF and non-climatic elements such as land under CP, and RP on agricultural output. We followed the model specifications of (Chandio et al., 2022), and (Warsame et al., 2021). In our model specifications, we also used additional control variables like Land under CP and agricultural labor. As a result, the functional relationship among CP, Land under CP (LD), RP, CO_2, RF, and TEM in Somalia is expressed as follows:

$$CP= F\,(LD,\ RP,\ CO_2,\ RF,\ TEM) \tag{1}$$

We can write EQ 2 as follows:

$$CP_t = \alpha + \beta_1(LD)_t + \beta_2(RP)_t + \beta_3(CO_2)_t + \beta_4(RF)_t + \beta_5(TEM)_t + \varepsilon_t \tag{2}$$

Equation (2) is used to specify the model and measures the variables' growth rates. The growth rate is expressed as a percentage change, which is equivalent to using the equation's natural log form. The specified model followed (Chandio et al., 2022) as:

$$lnCP_t = \alpha + \beta_1\,(lnLD)_t + \beta_2\,(lnRP)_t + \beta_3\,(ln\ CO_2)_t + \beta_4\,(lnRF)_t + \beta_5\,(lnTEM)_t + \varepsilon_t \tag{3}$$

Where lnCPt is log CP, lnLDt is a log Land Under CP, lnRPt is a log RP, $lnCO_2$ (t) is log CO_2 emissions and, $lnTEM_t$ is a log average TEM. Moreover, ε_t =stochastic error term, subscript (t) shows that the model uses time-series data.

$$\begin{aligned}\Delta \ln CP_t &= \alpha_0 + \sum\nolimits_{i=1}^{p} \Delta\alpha_1 \left(\ln LD\right)_{t-k} + \sum\nolimits_{i=1}^{p} \Delta\alpha_2 \left(\ln RP\right)_{t-k} \\ &+ \sum\nolimits_{i=1}^{p} \Delta\alpha_3 \left(\ln CO_2\right)_{t-k} + \sum\nolimits_{i=1}^{p} \Delta\alpha_4 \left(\ln RF_2\right)_{t-k} \\ &+ \sum\nolimits_{i=1}^{p} \Delta\alpha_5 \left(\ln TEM_2\right)_{t-k} + \beta_1 (\ln LD)_{t-1} \\ &+ \beta_2 (\ln RP)_{t-1} + \beta_3 (\ln CO_2)_{t-1} + \beta_4 (\ln RF)_{t-1} \\ &+ \beta_5 (\ln TEM)_{t-1}\ \varepsilon_t\end{aligned} \tag{4}$$

Where α_0 denotes the intercept, α_k indicates the model's short-term and long-term effects. β_k stands for the long-run effect, p indicates the number of lags, Δ represents that the data is the first difference, and $\mathcal{E}_t$ is the error term. The model's hypothesis and the study's associated bounds test are:

H_0: $\beta_1=\beta_2=\beta_3=\beta_4=0$ (No long-run relationship)

H_1: $\beta_1\neq\beta_2\neq\beta_3\neq\beta_4\neq 0$ (Variables are co-integrated).

We begin by doing a limits test to rule out the possibility of co-integration. The estimated F-statistic is contrasted with the Pesaran (2001) and Pesaran et al. tabulated critical value (2001). If the test statistics exceed the upper critical value, the null hypothesis of a lack of a long-run connection can be rejected regardless of whether the underlying order of integration of the variables is 0 or 1. Similarly to this, if the test statistic is less than a lower critical value, the null hypothesis is still valid. However, if the test statistic falls within these two ranges, the conclusion cannot be made. When the sequence of the variables' integration is known and all the variables are I (1), the decision is based on the upper bound. Likewise, if all the variables are I (0), then the decision is made based on the lower bound.

To estimate the appropriate lag length for each variable, the ARDL technique generates $(P+1)_K$ number of regressions, where P is the maximum number of lags that can be employed and K is the number of variables in the equation. Next, if we discover evidence of a long-term link, we calculate the error correction model (ECM), which shows how quickly a short-term disruption causes long-term equilibrium to return. The standard ECM involves predicting the following equation:

$$\begin{aligned}\Delta lnCP_t &= \alpha_0 + \sum\nolimits_{i=1}^{p} \Delta\alpha_1 (\ln LD)_{t-k} + \sum\nolimits_{i=1}^{p} \Delta\alpha_2 (\ln RP)_{t-k} \\ &+ \sum\nolimits_{i=1}^{p} \Delta\alpha_3 (\ln CO_2)_{t-k} + \sum\nolimits_{i=1}^{p} \Delta\alpha_4 (\ln RF)_{t-k} \\ &+ \sum\nolimits_{i=1}^{p} \Delta\alpha_5 (\ln TEM)_{t-k} + \varnothing ECE_{t-1}\varepsilon_t\end{aligned} \tag{5}$$

Model diagnostic and stability tests are carried out to confirm the model's goodness of fit. The diagnostic test looks at the model's serial correlation, normalcy, and heteroscedasticity. One should examine a variety of diagnostic tests to support the robustness of an estimated model. These are typical diagnostic tests that look at a model's general behavior, the goodness of fit, stability, parsimony, and functional form. The serial correlation (LM) test, Heteroskedasticity (Breusch-Godfrey) test also, and Normality (Jarque-Bera) test is among the tests utilized in these applications. The Ramsey reset test is also applied to the functional form. In addition to the latter, the variance inflation factor for multi-collinearity may be helpful when multi-collinearity is present.

4. EMPIRICAL ANALYSIS AND DISCUSSION

4.1. Descriptive Statistics

A descriptive statistic is a summary that highlights characteristics from a group of data, such as measures of normality, dispersion, and central tendency. It is displayed in Table 2, which shows the RP has the highest mean (13.06098), As well, the TEM has the lowest mean (3.280911). The highest maximum and minimum readings for RF and TEM were found to be 13.80283 and 3.280911, respectively.

When compared to other variables, CP has the biggest standard deviation (0.372086), which indicates that its values deviate more from the mean. A further indication that the data are normally distributed comes from the Jarque-Bera test. However, the correlation coefficient demonstrates how linearly connected the two variables are. Table 2, also shows a correlation matrix. All non-climatic variables including RP and land under CP have a positive correlation with CP, whereas climate variables such as carbon, RF, and TEM have a negative correlation among them. Moreover, the correlation implies that none of the regressors are multicollinear.

4.2. Trend Analysis

Figure 2 demonstrates the results of CP, land, RP, CO_2, RF, and TEM by assuming a linear trend while running the trend of the variables to discover data volatility of variables against time.

4.3. Unit Root Test

A preliminary study of time-series data involves determining if the variable is stationary. Whenever a unit root problem with biased inferences can be found. To identify a unit root problem, the enhanced Dickey-Fuller (ADF) and Philips-Peron tests are used. However, the results of the unit root shown in Table 3 confirm that, except for $lnCO_2$, and lnRP, all the variables have unit root problems at level I (0). Yet, other than I (1), all other variables under scrutiny are stationary at the outset both the intercept and the intercept with the trend. Because all the variables are integrated at the first difference, we can move on to the next step of our estimation procedure. Findings give context that CP and land under CP are stationary at a 1% level of significance both at the level & first difference. While TEM is stationary at a 5% level of significance. Moreover, RP and RF are not stationary at level. So, all variables are integrated into order 1, but none of the variables are integrated into order 2. This study provides support for ARDL-bound testing. To examine the short- and long-term relationships between the variables in this study, it is advisable to apply the ARDL model in this particular order.

4.4. Autoregressive Distributed Lag Model

The results of Table 4 show that all independent factors significantly contribute to CP. R^2 is 0.608361, which indicates that the independent variables account for 60% of the variation in the dependent variable.

Table 2: Descriptive Statistics and Correlation Analysis

	LCP	LCO2	LRF	LLD	LRP	LTEM
Mean	12.524	6.412	5.624	4.148	13.061	3.294
Median	12.520	6.438	5.622	4.172	13.114	3.292
Maximum	13.272	6.593	5.854	4.253	13.803	3.308
Minimum	11.686	6.194	5.439	3.998	12.468	3.281
Std. Dev.	0.372	0.100	0.100	0.082	0.299	0.007
Skewness	-0.243	-0.524	0.395	-0.488	0.057	0.330
Kurtosis	2.515	2.664	3.226	1.828	2.875	2.333
J-B	0.589	1.514	0.843	2.906	0.036	1.102
Prob.	0.745	0.469	0.656	0.234	0.982	0.576
Observation	30	30	30	30	30	30
Correlation Matrix						
LCP	1.000					
LCO2	-0.261	1.000				
LRF	-0.160	0.125	1.000			
LLD	0.359	-0.357	-0.531	1.000		
LRP	0.740	-0.317	-0.154	0.597	1.000	
LTEM	-0.236	0.174	0.346	-0.652	-0.276	1.000

Figure 2: Trend analysis of the variables

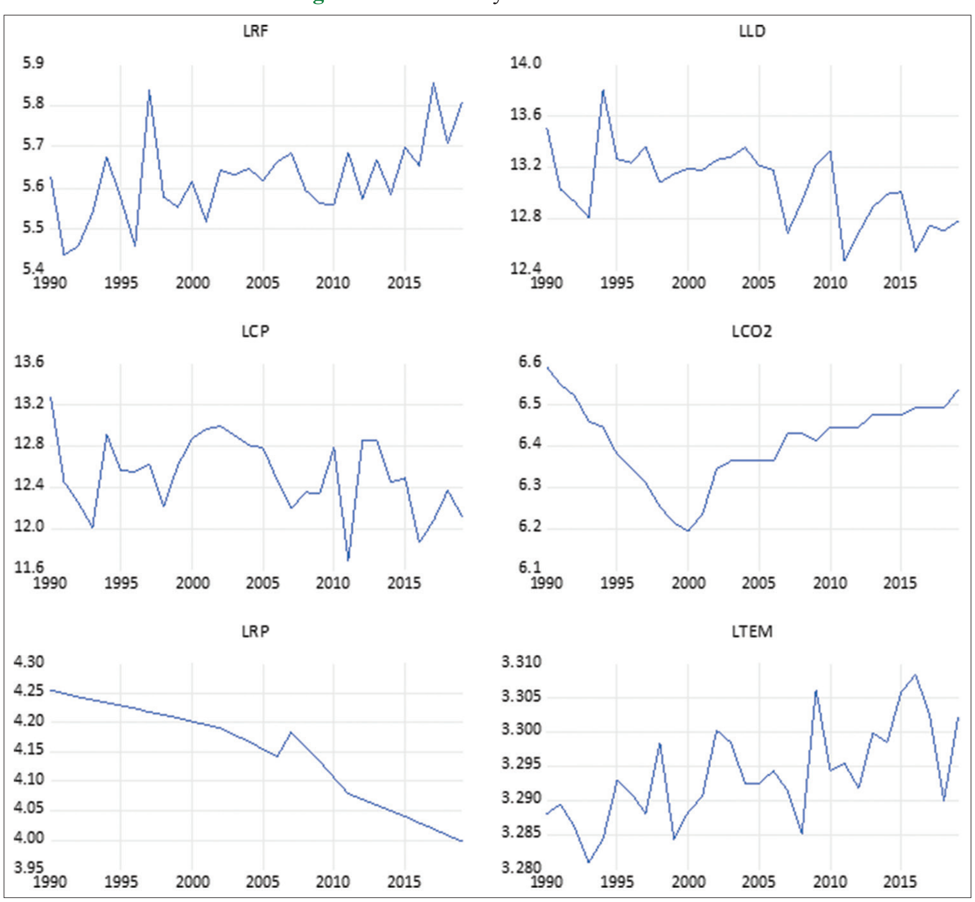


Table 3: Stationarity Test

Variable	Augmented Dickey-Fuller (ADF)		Phillips Perron (PP)	
	Intercept	Intercept & Trend	Intercept	Intercept & Trend
At Level				
lnCP	-4.541***	-4.671***	-4.614***	-4.709***
lnRP	0.820	-1.757	1.624	-1.625
lnLD	-3.730296***	-4.340571***	-3.746791***	-4.770634***
lnCO2	-1.49800	-2.445099	-1.783781	-2.438741
lnRF	-2.418730	-6.049188***	-4.229388***	-6.027057***
lnTEM	-3.395270**	-5.341222***	-3.325823**	-10.71731***
First Difference				
lnCP	-8.251953***	-8251953***	-14.20022***	-15.76032***
lnRP	-4.950846***	-5.139095***	-4.953396***	-6.279020***
lnLD	-6.421233***	-6.740787***	-14.25164***	-15.89033***
lnCO2	-3.033673***	-3.579644*	-2.950086*	-3.594164**
lnRF	-9.892106***	-9.701457***	-16.7076***	-16.45078***
lnTEM	-4.886955***	-4.742522***	-23.00554***	-22.26017***

Note: ***, ** and * denotes significant at 1%, 5% and10% significance level, respectively.

Table 4: ARDL Model Estimation

Variables	Coefficient	Std. Error	t-statistics	Prob.*
CP(-1)	0.271	0.139	1.951	0.064
LD	0.448	0.104	4.298	0.000
RP	-12476	4789.5	-2.605	0.012
CO2	-590.8	253.55	-2.330	0.029
RF	-685.9	529.46	-1.296	0.209
TEM	-145204	95310	-1.523	0.142
C	5239470	2771393	1.891	0.072
R-squared	0.608361	Akaike info criterion 25.21388		
Adjusted R-squared	0.50155	Durbin-Watson stat 1.899877		
Log-likelihood	-358.601	Prob (F-statistics) 0.001068		
F-Statistic	5.695689			

Table 5: F-Bounds Test

Model F-statistic		Significance	Bounds test critical values	
			K=5, n=30	
			I (0)	I (1)
lnCP=f (lnLD, lnRP, lnCO2, lnRF, lnTEM)	4.058226	1%	4.54	6.37
		5%	3.04	4.443
		10%	2.58	3.858

Table 6: Long Run Coefficient Elasticities

Dependent Variable=LnCP		
Regressors	Coefficients	t-statistics
C	67.79519	1.975325
LnCO2	-0.935566	-1.6712683
LnLD	0.988832***	4.932575
LnRP	-2.818941**	-2.519213
LnRF	-0.757291	-1.370028
LnTEM	-14.619947	-1.519409

**, **, and * exert significance level at 10%, 5%, and 1%.

The F-statistic value is likewise significant at a 5% level of significance, proving the overall suitability of the model.

Before starting to regress the model's co-integration, consider how the land under CP, RP, CO_2, RF, and TEM affect Somalia's CP. We must select the ideal lag length using Hendry's general to a calculated strategy. According to our sample size, which is roughly 30 observations, starting with the minimum lag order (1) and moving up to lag (2) until

Table 7: Short-run Dynamic Effect and Error Correction Model (ECM)

Dependent Variable=LnCP		
Regressors	Coefficients	t-statistics
C	-0.003699	-0.07152
ΔLnCPt-1	-0.095295	-0.93597
ΔLnCO2t-1	-1.970499	-1.6276
ΔLnLDt-1	0.8775999***	6.387247
ΔLnRP t-1	-1.076555	-0.29838
ΔLnRF t-1	-0.454356	-1.39068
ΔLnTEM t-1	-11.45327**	-2.0525
ECM(-1)	0.925806***	4.00978

**, **, and * exert significance level at 10%, 5%, and 1%

Table 8: Diagnostics of Estimated ARDL Model

Diagnostics	Test Applied	Prob.
Serial Correlation Test	LM Test	0.8657
Normality Test	Jarque-Bera	0.127321
Heteroscedasticity	Breusch-Pagan Godfrey	0.6655
Functional form	Ramsey's reset test	0.7992

the model is stable and the best lag order is free of diagnostic errors. We regress Eq. (4) to the Bound test after completing the unit root and selecting the best lag model to find a long-run co-integration among the variables, as indicated in Table 5. Unfortunately, small sample research cannot employ the critical values created by (Pesaran et al. 2001). Due to the limited number of observations (30) in our sample, we employed Narayan critical values to determine co-integration in our analysis. Narayan (2004) asserts that a small sample of observations between 30 and 80 can be used to determine critical value.

Moreover, Table 5 demonstrates the long-term co-integration of CP with land under CP, RP, CO_2, RF, and TEM.

Yet, we fail to reject the alternative hypothesis (co-integration) and reject the null hypothesis (no co-integration). Bound F-statistics of 4.058226 indicates evidence of co-integration between the dependent variable and explanatory factors if it is bigger than the crucial value of 3.858 at a significance level of 10%.

Long-run coefficient elasticities of the variables can be determined after determining the co-integration of the long-run among the variables. The long-term correlations between climate and non-climate variables including CO_2, RF, TEM, land under CP, RP, and CP respectively are shown in Table 6. We have evidence that some explanatory factors and the dependent variable exhibit long-run co-integration, or long-term movement in the same direction.

However, climate factors have no significant effect on CP in Somalia including TEM, CO_2, and RF. The result of this study shows that only non-climate factors are a significant determinant of Somalia's CP including RP and land under CP. According to Table 6's interpretation, the RP has a significantly negative impact on CP; which means that a 1% increase in RP decline cereal yield by 2.8% in the long run. In case, the RP in Somalia has grown significantly in the past few decades, leading to increased demand for food and pressure on the agricultural sector. Moreover, chronic food insecurity and conflict have also led to significant population displacement, affecting CP and food security. Mover, the RP can impact CP in several ways. More people living in rural areas can lead to increased demand for cereal crops, which may increase production. However, if population growth outstrips the ability of the agricultural sector to provide enough food, it can lead to increased food insecurity and malnutrition.

Although, land under CP has a significantly positive impact on CP. The long-term coefficient of land under CP indicates that a 1% increase in land under CP will increase CP by 0.99%. According to (Dogan, 2018; Ahsan et al., 2019) reported that land under CP has a significantly positive impact on CP. On the other side, Land degradation and desertification have been ongoing challenges in Somalia that have reduced the amount of land suitable for CP. In addition, conflict and displacement have led to land grabbing and land use changes that have further impacted CP. The amount of land devoted to CP can directly impact the total cereal output in Somalia. However, this factor may also interact with others, such as RF and TEM, as land that becomes less suitable for CP due to environmental changes may lead to decreased yields.

In this study, climate factors including CO_2, RF, and TEM have no significant impact on CP in Somalia. Although, Somalia has a long history of droughts and erratic RF patterns. For example, in the 1970s and 1980s, a series of severe droughts led to widespread crop failures, livestock losses, and famine, which resulted in the deaths of thousands of people. Insufficient RF can reduce yields and even lead to crop failure. On the other hand, excessive RF can also be detrimental to cereal crops by causing flooding and soil erosion. Overall, the historic impacts of these factors have contributed to the challenges facing Somalia's CP and food security. Addressing these challenges will require long-term efforts to build resilience and sustainability in the agricultural sector, as well as addressing the underlying social, political, and environmental drivers of insecurity and vulnerability.

After the long-run co-integration, the short-run dynamic effect and error correction term (ECT) are calculated. Table 7 demonstrates the error correction term and short-run dynamic effect co-integration among the variables. According to Table 8, lag (1)/previous year CP improves the current CP by 0.095%. Apart from land under CP, and TEM are significant effect CP in the short term, while others are not. A 1% increase in TEM, will minimize CP by 11.45%. Moreover, land under CP effects positively CP with a 1% increase in land under

Figure 3: Summary of the long-run relationship between the selected variables

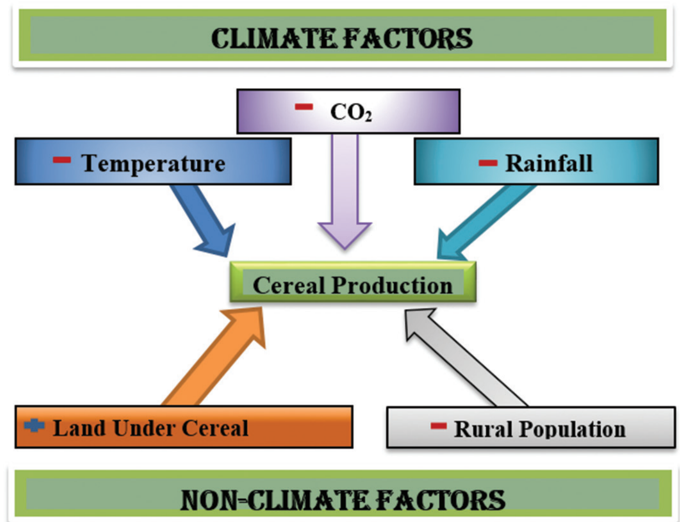
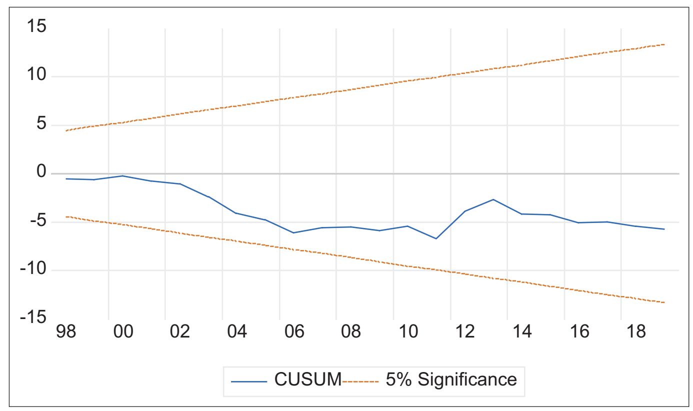


Figure 4: CUSUM



CP, will improve CP by 0.88% in the short run. Most importantly, the ECM coefficient captures the speed of adjustment of the dependent variable toward its long-run equilibrium value in response to any deviations from the equilibrium in the short run. A positive ECM coefficient (0.925) indicates that 0.92% of the production of cereal adjusts positively towards the equilibrium in the short run. In other words, if the CP deviates from its equilibrium value, it will adjust positively towards its long-run equilibrium value in the short run.

4.5. Diagnostics Test

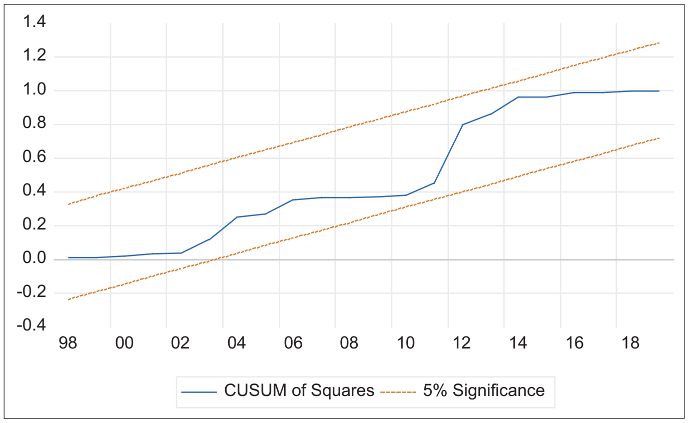
As seen in Table 8, many econometric issues, including autocorrelation, heteroscedasticity, and normal distribution, are not present. Similarly, there is no functional form model specification error.

The cumulative sum of recursive residuals and the cumulative sum of squares of recursive residuals are depicted in Figures 3 and 4, respectively. The fact that CUSUM and CUSUMSQ are both inside 5% of the crucial boundaries indicates that the model is structural.

5. CONCLUSION

Based on the ARDL modeling of climate and non-climate factors affecting CP in Somalia, none of the researchers have searched

Figure 5: CUSUM square



those factors. This article studied that both climatic and non-climatic factors significantly affect CP in the country. Therefore, the present empirical study fills this gap in climatic and non-climatic literature. The study specifically looked at the impact of five variables on CP: CO_2, TEM, RF, land under CP, and RP from 1990 to 2019. The weakness in this study is that other key non-climate factors that affect cereal productivity were not taken into account. For an instant, in our research, we failed to include energy consumption and fertilizer which are effective factors that affect production because of insufficiency of data availability. To utilize an ARDL model first we did a bound test to know if there is a long-run co-integration of variables. Then, we perform long-run and short-run co-integration, and the result indicated that climate factors have no significant effect on CP in Somalia including TEM, CO_2, and RF.

The result of this study shows that only non-climate factors are a significant determinant of Somalia's CP including RP and land under CP in the long run. Additionally, the study found that land under CP and RP also have a significant impact on CP in Somalia. The results indicate that increasing the amount of land under CP and having a larger RP can have positive effects on CP, likely due to increased agricultural productivity. This suggests that other factors, such as non-climate variables, are more important determinants of CP in the country. While in the short run TEM and land under CP have significantly impacted CP. All variables harm CP except land under CP which has a positive effect both in the long run and short run.

This study highlights the complex and interrelated factors that affect CP in Somalia. The results of this study can inform policy interventions aimed at enhancing CP and improving food security in Somalia. These findings have important implications for policymakers and stakeholders in Somalia's agricultural sector. Firstly, the negative impact of RP on CP suggests that policymakers need to address population growth by implementing policies aimed at reducing rural-urban migration, promoting family planning, and investing in education and job creation in rural areas. Secondly, the positive impact of land under CP on CP suggests that there is a need for increased investment in land management practices to ensure that land is utilized efficiently and sustainably.

In conclusion, the study's findings suggest that policymakers need to take a holistic approach to address the challenges facing Somalia's agricultural sector. This should include, addressing population growth, and investing in land management practices.

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