Examining the Effects of Climate Change and Political Instability on Maize Production in Somalia

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Examining the effects of climate change and political instability on maize production in Somalia

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Abstract

Agricultural production is sensitive to climate variabilities, so climate change-agriculture sector nexus is topical in developing countries. Given that, this study models the impact of climate change variables – rainfall and temperature – on maize production in Somalia. The study also incorporates political instability as a main determinant variable of maize production. Several econometric methodologies – Johansen and Juselius cointegration, Fully modified ordinary least square (FMOLS), Canonical cointegration regression (CCR), variance decomposition (VD) and impulse response function (IRF) – were espoused with a time series data spanning between 1980 and 2018. The empirical results of Johansen and Juselius cointegration show that the explanatory variables are cointegrated to the maize output in the long-run. The study also revealed that average temperature and political instability significantly inhibit maize production in the long-run. Whereas rainfall has a favourable effect on maize production in the long-run. Furthermore, land degradation and land area under maize cultivation – incorporated in the model as control variables – are observed to have positive effects on maize production in the long-run. Based on these findings, the study emphasizes

the importance of the de-escalation of conflicts and the implementation of irrigation facilities which will enhance the productivity of maize crop production.

Keywords: Maize production, Temperature, Rainfall, Somalia

1. Introduction

There is consensus among scholars and researchers that climate change plays a significant role for agricultural productivity. Since the world is experiencing a massive population growth, fast urbanization, changes to dietary pattern, and increasing incomes (Ayanlade & Ojebisi, 2020; Mihiretu, Okoyo, & Lemma, 2019; Thornton et al., 2009), it is expected that the demand for food, including cereal crops, will rise significantly in the near future. Thus, in order to satisfy human nutrition needs, the cereal crops, especially maize must rise since it is one of the most important food sources for human consumption. However, the negative effect of climate change — changes in rain pattern, rising temperature, and floods — on crop production is a great challenge for agriculture sector to meet the ever-increasing demand for its products.

There are ample empirical evidences (Abbas & Mayo, 2021; Pickson et al., 2020; Shayanmehr et al., 2020; Warsame et al., 2021) who documented out the negative impact of climate change on crop production in both developed and developing countries, however these studies report that the adverse effect of climate change is more felt in developing countries, especially agriculture-based countries (Shayanmehr et al., 2020). Using Ricardian analysis and quantile regression, Migliore et al. (2019) pointed out that climate variations have enormous impact on the yields of major crops grown in Sicilian region, Southern Italy. Pickson et al. (2020), in his study of China, found out that CO₂ emissions, average temperature, and temperature variability have a significant negative impact on cereal production. This finding is also supported by Chandio et al. (2020) who documented out that temperature and rainfall influences china's agriculture production adversely. Similarly, Porter and Semenov (2005) and Zhao et al. (2017) discovered that maximum temperature and water variabilities have detrimental effect on crop yields. Wheeler and Von Braun (2013) argued that rising temperature and changes in rainfall pattern are still the main factors that determine agricultural productivity of countries even though there is a continuous technological progress.

Amin et al. (2015) found out that temperature and rainfall have significant negative impact on permanent crops cultivated in Bangladesh, particularly the rice and wheat yields. Xu et al. (2016)

estimated decrease in maize yield in Iowa, USA from 20th century to the 21st century by employing simulation and linear regression models. The results from all simulation models show that a maize yield decline of 15% to 50% from late 20th century to middle and late 21st century, while the results of linear regression revealed that 1°C rise in temperature leads to 6% state-averaged maize yield decline. Similarly, using simulation models, Luhunga (2017) reported similar results in his study of Tanzania. Specifically, the simulations predicted a maize yield decrease of 3.1% and 5.3% under two Representative Concentration Pathways. Sarkodie & Owusu (2017) concluded his study in Ghana that there is a significant long-run association between climate change, measured in carbon dioxide, and agriculture production. Chandio et al. (2020) reported a similar results in Pakistan. Ali et al. (2017) investigated the effect of climatic variations on permanent crops of Pakistan, namely sugarcane, rice, maize, and wheat and found out that rising temperatures and rainfall have negative and significant impact on these crops. However, the results showed that rainfall have a positive and significant effect on wheat, thus confirming our argument that different crops react to climate variations differently.

In the context of Somalia, it is considered one the countries who are extremely susceptible to climate variations, even though the agriculture sector still remains the backbone of the Somali economy since it contributes to GDP and country's total export earnings by approximately 75% and 93%, respectively (Warsame et al., 2021). More precisely, changes in temperature are associated with reducing soil moisture, causing evaporation, drier conditions, and rain failures. This would ultimately decrease water availability for irrigation which further causes crop yields to decline sharply (Warsame et al., 2021). Specifically, the lower Shebelle region which is the country's principal maize production region experiences temperatures ranging from 26 to 28°C (Ryan et al., 2018). This could have a negative impact on maize yield which is one of the most important crops in Somalia. Similarly, Somalia farmers heavily depend on rainfall for growing crops since the availability of other means such as drilling is limited. Consequently, the maize production decreases sharply in the times of rainfall failures (Warsame et al., 2021).

In addition to climatic variations, political instability poses another imminent threat to the Somalia's agriculture sector, especially maize producing regions. This is because farmers face severe taxation burdens since they are required to pay the tax to different authorities such as the federal government of Somalia, armed militias belonging to clans, and Al-Shabab terrorist group— a terrorist group that operates mainly in Somalia and have affiliation with Al-Qaeda. Thus, these excessive taxations make

the farming business unprofitable, risky, and costly. Also, the political instability situation in these regions made interventions by aid agencies extremely challenging and impossible. Thus, this forced to many farmers stop farming activities and displace out of these regions (FAO & World Bank, 2018).

As evidenced by figure 1, maize production in Somalia exhibits a trending volatility from 1960 to 2019. Maize production was quietly stable during 1960-1970 period, but from 1972 to 1974 it dramatically declined due to the droughts occurred in Somalia in the earlier of 1970s. However, it immediately recovered in the following years in which maize output reached to a record level high of 353,300 tons in 1988. Following the ousting of the military government in 1991, maize production has substantially decreased from 315,000 in 1990 to 100,000 tons in 1991. This is chiefly owing to the civil wars broke out in Somalia in 1991. Maize output soared to a record level high – 287,500 tons – in 2001 and 2002 since the collapse of the central government in 1991, but it declined to a record low level of 100,000 tons in 2006. This reduction is attributed to the beginning of the war between Islamic Courts Union (ICU) and Transitional Federal Government of Somalia supported by the Ethiopian military. Moreover, a destructive drought – in which later turned into famine – occurred in 2011 reduced maize production from 132,627 in 2010 to 65,126 thousand tons in 2011. And beyond this period, maize production has been declining. Hence, it is notable that maize production in Somalia is inhibited by political instabilities, recurrent droughts and floods induced by climate change.

Figure 1: Maize production

Source: FAO (2019)

Despite the adverse effect of climate change and political instability on maize production, Somalia yet lacks strategies and adaptation policies to mitigate the unfavorable effect of climate changes on maize production. This might be because of political instability that prevents from aid agencies and federal government of Somalia to devise adaptation and intervention policies that are aimed at improving water availability, irrigation facilities and implementing good agriculture practices. In addition to this, the number of empirical studies assessing the relationship between climate change and agriculture production in Somalia is very few, thus making difficult to design a coherent agricultural policy since the scientific evidence that would guide the formulation of such policies or strategies is rare. Therefore, this study aims to evaluate the impact of climate change variables, namely temperature and rainfall, and political instability along with other control variables on maize production in Somalia for the period between 1980 and 2018.

Moreover, this study differs from the study of Warsame et al. (2021) which was the first study investigated the issue empirically and systematically in many ways. First, Warsame et al. (2021) used crop production index, which is aggregate, to measure agriculture production. However, by doing so, it is a bias resulting from the aggregation since climate change affects different crops in a different manner; therefore, this study tries to solve this aggregation bias by using individual crop to measure agriculture production properly and draw suitable policy implications. In such a case, we

use maize since it is the third most consumed crop in Somalia after Staple food crops and sorghum which amounted 23% between 2016-2017 (FAO & World Bank, 2018). Furthermore, the study of Warsame et al. (2021) failed to include political instability variable in their model which has an adverse effect on the agriculture sector.

Following this section, subsequent sections include data source and econometric model employed, results of the econometric model, summary, and policy implications.

2. Methodology and Data Sources

2.1. Data

To achieve the objective of this study, we used annual time series data that ranges from 1980 to 2018, and it was obtained from world bank and FAO. The study used maize production as the dependent variable; while rainfall, temperature, land degradation, political instability, and maize area under cereal are the regressors. Subsequently, all the variables were converted into a natural logarithm to mitigate heteroskedasticity. The descriptions and sources of the variables utilized in this study are illustrated in Table 1.

Table 1. Variable descriptions and sources

Variable	Symbol	Unit of measurement	Source
Maize production	MP	Thousand tons	FAO
Rainfall	AR	Average annual precipitation (mm)	World Bank
Temperature	AT	Average annual temperature in (°C)	World Bank
Political Instability	PIS	It is a dummy variable. We gave a value of '0' during the political stability period, and a value of '1' during the political instability period.	
Land Degradation	LD	Million hectares	World Bank
Maize area under cultivation	MUC	Square Kilometer area	FAO

2.2. Econometric modelling

To empirically investigate the long-run effect of climatic and non-climatic factors on maize production in Somalia, we utilized the work of Adelaja & George (2019), Warsame et al. (2021), Chandio et al. (2020), and Chandio et al. (2021). Therefore, we specified the model as follows:

$$\ln MP_t = \beta_0 + \beta_1 \ln AR_t + \beta_2 \ln AT_t + \beta_3 LD_t + \beta_4 \ln MUC_t + \beta_5 PIS + \varepsilon_t \quad (1)$$

$\ln MP_t$ is the log of maize production in year t , $\ln AR_t$ is the log of average rain in year t , $\ln AT_t$ is log of average temperature in year t , $\ln LD$ is log of land degradation in year t , $\ln MUC_t$ is the log of maize area under cultivation in year t , PIS is a dummy variable that captures the effect of political instability on maize production, by giving a value of '0' during political stability and a value of '1' political instability and ε_t is the error term in time t .

Before checking whether there is a cointegration in our model and estimating it, there is prerequisite step which has become a common practice in time series analysis. This is to perform unit root analysis to prevent from obtaining spurious results. Thus, we utilized Augmented Dickey Fuller (ADF) and Philips Perron (PP) tests to determine the order of integration of our scrutinized variables. If our variables are integrated of order one or $I(1)$, then we can proceed to examine the presence of cointegration in our model. Hence, Johansen and Juselius (1990) cointegration method will be employed for this purpose. The advantage of applying Johansen and Juselius cointegration approach is that it uses a maximum likelihood technique to determine the number of cointegrating vectors in unrestricted vector autoregressive (VAR) system. Equation (2) illustrates the error correction form of this process:

$$\Delta Y_t = \Pi Y_{t-k} + \sum_{i=1}^{K-1} \Gamma_i \Delta Y_{t-1} + \mu + \varepsilon_t \quad (2)$$

Where ΔY_{t-1} denotes first difference of an $(n \times 1)$ vector of the n variables, Π and Γ represents the coefficients of the matrix that will be estimated, μ stands for a vector of constant, Y_{t-1} denotes the past values of Y_t , and ε_t is vector of white noise residuals. Indeed, the steps involved in applying Johansen and Juselius (1990) cointegration method is a straightforward. It first determines the rank of matrix Π because it carries important information that associated with both the long-run and speed of adjustment. Hence, the cointegrating rank matrix Π can be formulated as follows:

$$\Pi = \alpha \beta' \quad (3)$$

where α is the vector of speed of the adjustment, while β is the vector of long-run equilibrium if only if the rank of matrix Π equals one; thus, confirming the existence of cointegration relationship between the variables of interest in the model. To put it another way, it can be concluded that there is one single cointegrating vector or one linear combination in which Y_t is integrated of order one or I (1), however the linear combination of $\beta'Y_{t-1}$ is integrated of order zero or I (0) which is stationary.

Subsequently, following the work of Johansen (1988) we employed trace and maximum eigen value statistic tests to estimate the number of cointegrating vectors which takes the following specification form:

$$\lambda_{trace} = -T \sum_{i=r+1}^n \ln(1 - \lambda_i^2) \quad (4)$$

$$\lambda_{max}(r, r + 1) = -T \ln(1 - \lambda_{r+1}) \quad (5)$$

Where the value of λ_i is obtained from the estimated matrix and T represents the number of observations after lag adjustment. Moreover, the null hypothesis is specified as; the variables are not co-integrated in the long-run, whilst the alternative hypothesis; the series are co-integrated in the long-run. We conclude that there is no cointegration relationship in our model if the t-statistics of these two tests are greater than the critical value of each test.

After ascertaining the long-run cointegration among variables of our model, the next step is to estimate long-run coefficient elasticities of the variables. Thus, we utilized fully modified ordinary least squares (FMOLS) method to serve for this purpose. We selected this method because it has the ability to tackle with serial correlation problems. Generally, to estimate the long-run coefficient elasticities of the variables using FMOLS; y_t (the dependent variable) and X_t (is a vector of independent variables where X_t is an $M \times 1$ vector and $T = 1, 2, 3, \dots, T$) should satisfy the following condition:

$$Y_t = X_t' \beta + d_t' \alpha + \mu_{1t} \quad (6)$$

$$X_t = X_{t-1} + \mu_{2t} \quad (7)$$

Where d_t is a vector of deterministic trend regressors; $\mu_t = (\mu_{1t}, \mu_{2t})'$ are the error terms. Following this, Λ and Ω , which are the long-run covariance matrix, can be estimated by using the following two equations.

$$\Lambda = \sum_{i=0}^{\infty} E(\mu_t \mu'_{t-1}) = \begin{bmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & \Omega_{22} \end{bmatrix} \quad (8)$$

$$\Omega = \sum_{i=-\infty}^{\infty} E(\mu_t \mu'_{t-1}) = \begin{bmatrix} \Phi_{11} & \Phi_{12} \\ \Phi_{21} & \Lambda_{22} \end{bmatrix} \quad (9)$$

Subsequently, suppose $Y_t^+ = Y_t - \widehat{\Phi}_{12} \widehat{\Omega}_{22}^{-1} \Delta X_t$; $\widehat{\lambda}_{12}^+ = \widehat{\lambda}_{12} - \widehat{\Phi}_{12} \widehat{\Lambda}_{22} \Delta X_t$, where $\widehat{\lambda}_{12}$, $\widehat{\Phi}_{12}$, $\widehat{\Omega}_{22}^{-1}$, and $\widehat{\Lambda}_{22}$ are estimated parameters. Thus, The FMOLS estimator is given as follows:

$$\begin{bmatrix} \widehat{\beta} \\ \widehat{\alpha} \end{bmatrix} = (\sum_{t=1}^T z_t z_t')^{-1} \left(\sum_{t=1}^T z_t y_t - T \begin{bmatrix} \widehat{\lambda}_{12}^+ \\ 0 \end{bmatrix} \right) \quad (10)$$

Where $z_t = (x_t', d_t')'$

3. Empirical Analysis and Discussion

3.1. Descriptive Statistics

Table 2 summarizes the summary statistics and correlation of the interested variables of the study. Maize and land under maize cultivation have highest average values of 11.98 and 11.97, respectively. In the same vein, they are observed to have the highest median and maximum values compared to other variables. Moreover, political instability has the lowest minimum value of 0 due to that its dummy variable created – given 0 and 1. The highest standard deviation values are shown by land under maize cultivation (0.49) and maize production (0.48) which implies that how their average values are scatter from its normal values. Further, land degradation and average temperature are positively skewed, whereas rainfall, maize, land degradation and land under maize cultivation are negatively skewed. The Jarque-Bera points out that land degradation and political instability are not normally and identically distributed, whereas the rest of the variables are normally and identically distributed.

Besides, Table 2 also presents the correlation of the scrutinized variables. It is found a positive correlation between maize and land degradation, maize and land under maize production. Contrary to that, average temperature, average rainfall and political instability are established to have negative correlations with maize production. In addition, land degradation is observed to have a positive correlation with average temperature, average rainfall and political instability, and a negative relationship with land under maize cultivation. Regarding to climate variables, average temperature

has a positive relationship with average rainfall and political instability, and a negative relationship with land under maize cultivation. There is a positive relationship between rainfall and land under maize cultivation. Political instability is negatively correlated with rainfall and land under maize cultivation.

Table 2: Descriptive Statistics

	lnMP	lnLD	lnAT	lnAR	lnMUC	PIS
Mean	11.98798	13.87661	3.301822	3.109788	11.97417	0.702703
Median	11.89136	13.84991	3.301953	3.103335	12.14666	1.000000
Maximum	12.77507	14.11562	3.334483	3.509205	12.80050	1.000000
Minimum	11.00210	13.79938	3.276998	2.656198	10.50183	0.000000
Std. Dev.	0.482871	0.078576	0.012893	0.191617	0.492642	0.463373
Skewness	-0.027885	1.795578	0.378609	-0.075417	-0.815656	-0.886969
Jarque-Bera	1.429875	31.35381	0.912192	0.068420	4.232676	7.120832
Probability	0.489223	0.000000	0.633753	0.966369	0.120472	0.028427
Correlation						
lnMP	1					
lnLD	0.0744	1				
lnAT	-0.3278	0.4242	1			
lnAR	-0.0148	0.1679	0.1274	1		
lnMUC	0.7403	-0.0038	-0.3274	0.0921	1	
PIS	-0.5307	0.4564	0.4922	-0.0069	-0.4527	1

Std. Dev represents standard deviation.

3.2. Unit Root Test

To circumvent biased and incorrect inferences, two-unit root tests – Augmented Dickey-Fuller (ADF) and Philips Perron (PP) – were employed. Nevertheless, the outcome of the unit root presented in Table 3 certifies that all the variables contain unit root problem at level I (0) except average rainfall (lnAR). But, all other scrutinized variables are stationary at first difference I (1) both intercept and intercept with trend. Hence, we are eligible to proceed the next step of our estimation method, since all the variables are integrated at first difference $I(1)$.

Table 3. Unit Root Tests

Variable	ADF		PP	
	Level		Level	
	Intercept	Intercept & Trend	Intercept	Intercept & Trend
lnMUC	-2.8894*	-4.1069**	-2.9499**	-4.0874**
lnMP	-2.0394	-3.1723	-2.0687	-3.1723
lnAT	-2.7240	-5.9612***	-2.5689	-6.5323***
lnAR	-6.6817***	-6.7283***	-6.8118***	-7.7236***
lnLD	-2.8371*	-3.2499*	-2.1353	-2.3756
PIS	-1.6299	-1.5753	-1.6276	-1.5753
	First difference		First difference	
	Intercept	Intercept & Trend	Intercept	Intercept & Trend
lnMUC	-8.4774***	-8.3638***	-13.8108***	-14.1695***
lnMP	-7.1538***	-7.2022***	-7.1801***	-7.2463***
lnAT	-9.4082***	-9.3523***	-17.5761***	-22.8945***
lnAR	-8.2120***	-4.0958**	-27.1397***	-36.3110***
lnLD	-4.7555***	-4.6894***	-6.3876***	-6.6082***
PIS	-6.1644***	-6.2071***	-6.1644***	-6.2187***

262

Notes: ***, ** and * indicate significance level at 10%, 5% and 1% respectively.

263 Subsequently after the confirmation of the variables' stationarity, we need to determine the best
 264 optimal lag length. It replicates the dynamic characteristics of the model. Several lag selection
 265 criteria – Final prediction error (FPE), Akaike information criterion (AIC), Schwarz information
 266 criterion (SC), and Hannan-Quinn information (HQ) – were adopted. Thus, the result is presented
 267 in Table 4, and lag 1 is set up as the optimal lag length, since it has the lowest values of all lag
 268 selection criteria.

269

270

Table 4: Optimal Lag Selection

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Lag	LogL	FPE	AIC	SC	HQ
1	204.9906	4.42e-12*	-9.1346*	-7.5673*	-8.5821*
2	233.3352	7.60e-12	-8.7208	-5.5861	-7.6157

3	275.1428	8.24e-12	-9.0348	-4.3326	-7.3770
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* indicates lag order selected by the criterion.

Next, we estimate Johansen & Juselius (J&J) co-integration method after determining the optimal lag length. Maximum Eigenvalue and Trace test values are compared with critical values to establish a long-run co-integration between the variables. The statistical values of the co-integration – Trace and Maximum Eigen value – indicate that the variables are co-integrated in the long-run. Therefore, the results reported in Table 5 shows that there is at least one co-integrating vector in the long-run in both tests.

Table 5: J&J cointegration test result

Hypothesized	Trace Test	Test Statistic	5% Critical Value	Prob.**
$r \leq 0^*$		112.5852	95.75366	0.0021
$r \leq 1$		50.17602	69.81889	0.6301
$r \leq 2$		26.16500	47.85613	0.8839
$r \leq 3$		12.07394	29.79707	0.9293
$r \leq 4$		6.005991	15.49471	0.6948
$r \leq 5$		2.881027	3.841466	0.0896
Maximum Eigenvalue Test				
$r \leq 0^*$		62.40920	40.07757	0.0000
$r \leq 1$		24.01102	33.87687	0.4548
$r \leq 2$		14.09105	27.58434	0.8163
$r \leq 3$		6.067951	21.13162	0.9815
$r \leq 4$		3.124963	14.26460	0.9381
$r \leq 5$		2.881027	3.841466	0.0896

Trace test and Max-eigenvalue test indicate 1 cointegrating equation at the 0.05 level. * denotes rejection of the hypothesis at the 0.05 level.

After verifying that the variables are co-integrated in the long-run, we subsequently estimate the long-run coefficients of the parameters by utilizing FMOLS and CCR as robustness. FMOLS results presented in Table 6 revealed that land under maize production, average rainfall and land degradation are positively and significantly co-integrated with maize production in the long-run. Conversely, average temperature and political instability are adversely related to maize production, even though political instability is statistically insignificant. Interpretively, a 1% increase in land under maize production, average rainfall and land degradation enhance maize production by about

0.64%, 0.69% and 2.44%, respectively, in the long-run. Furthermore, average temperature inhibits maize production by about 13.66% for 1% increase in average temperature. This finding sheds the light on that temperature has a massive adverse influence on maize production in Somalia.

However, relying on a single estimation method can lead to biased policy inferences; thus, we re-estimate the long-run coefficient of the parameters to find robust results by using CCR estimation method. The CCR results reported in Table 6 revealed that land under maize production, average rainfall and land degradation have favorable effect on maize production in the long-run. In addition, average temperature and political instability significantly hamper maize production in the long-run. When it comes to the interpretation of coefficient elasticities of the CCR results, a 1% increase in land under maize production and land degradation contribute to maize production to rise by about 0.41% and 3.03%, respectively, in the long-run. But average rainfall is not different from zero which implies that it's statistically insignificant. Contrary to that, a 1% increase in average temperature undermines maize production by 15.08% in the long-run. Interestingly, political instability hampers maize production by about 0.37% in the long-run, if one unit rises in political instability. In summary, the long-run outcome of the FMOLS is verified by the results of CCR estimation method robustly.

Concerning the adverse effect of temperature and the favorable impact of precipitation on maize output is in line with the recent empirical studies. For instance, Chandio et al. (2021) discovered that rising temperature significantly reduced the rice production in major Asian countries, while the precipitation improved rice production. More specifically, this study is more consistent with the study of Warsame et al. (2021) – conducted in Somalia – who came to the conclusion that temperature and rainfall have a negative and positive effect on crop production, respectively. But, the impact of climatic variables – temperature and rainfall – on maize output are greater than that the aggregate crop production of Warsame et al. (2021) findings. They found that crop production is inhibited 11.5% by temperature rise in the long run compared to the maize – 15.8% (CCR results) and 13.66% (FMOLS results) in the long-run. In addition, a rise in precipitation improves crop production by about 0.30% compared to maize production – 0.70% – in the long-run. Hence, maize productivity is more sensitive to climatic variability such as; rainfall and temperature compared to aggregate crop production. Thus, this can be attributed that maize is the major cultivated crop in Somalia which depends on rainfall irrigation, and maize crop is more sensitive to climate shocks than other crops naturally. Nevertheless, our finding of negative effects of temperature on maize

crop is corroborated with previous studies (Luhunga, 2017; Xu, Twine, & Girvetz, 2016), and the favorable impact of rainfall agrees with previous findings (Guntukula & Goyari, 2020; Pickson, He, Ntiamoah, & Li, 2020).

Further, political instability adverse effect on agricultural production in general can be noticed in food insecurity and poverty situations of the prone-conflict Somalia population. Political instability escalates conflicts and wars which disrupts the supply of inputs and outputs as well as its distribution, leads to price shocks and causes widespread migration of labor due to insecurities. More importantly, political instability hampers both domestic and foreign investments in agriculture which sabotages the accomplishment of reaching full potential agriculture production. However, maize is largely cultivated in south and central region of Somalia, and it is notable that this region has been severely affected by conflicts compared to North and East regions of the country. Therefore, political instability rise undermines maize production. Thus, the adverse effect of political instability on agriculture production is supported by several previous studies who came to the same conclusion (Adelaja & George, 2019; Arias, Ibáñez, & Zambrano, 2018).

Table 6: Long-run coefficient elasticities

Dependent Variable: lnMP			
Method:	(FMOLS)	(CCR)	
Variable	Coefficient	Coefficient	
lnMah	0.6462*** (5.9762)	0.4161*** (2.7852)	
lnAVT	-13.6639*** (-3.2129)	-15.0813** (-2.0894)	
lnAVR	0.6979*** (2.9092)	0.3195 (0.6996)	
PIS	-0.1954 (-1.5047)	-0.3764** (-2.4730)	
lnLD	2.4484*** (3.4948)	3.0370*** (3.5678)	
Constant	13.3033 (0.9152)	13.9035 (0.6285)	
Adjusted R-squared	0.332544	0.4548	
S.D. dependent var	0.482871	0.4829	

374	S.E. of regression	0.394496	0.3566
375	Sum squared resid	4.824435	3.9408
376			

377 3.3. Impact Accounting

378 Shocks in climate variables have substantial effects on maize production in the short-run, and one
379 of the limitations of FMOLS and CCR are their lack of ability to capture this effect. Therefore, we
380 perform Variance Decomposition (VD) and Impulse Response Function (IRF) to account for the
381 shock effects of variables on each other and maize production.

382 The results of VD presented in Table 7 revealed that 63.57% of future fluctuations in maize
383 production is explained by historical dynamics in maize production, whereas 9.70% is responsible
384 for land area under maize production. In the same vein, maize production and land area under
385 maize production cause 32.8% and 48.5%, respectively, of future variations in land area under maize
386 production. Attributively, maize production and land area under maize cultivation are closely
387 related, and a rise in land area of maize cultivation contributes to an increase in maize output.
388 Further, future fluctuations in land degradation by 41.6%, 21.97% and 14.46% are due to historical
389 dynamics in land degradation, maize production and land under maize cultivation respectively.
390 Hence, this sheds the light on that agriculture cultivation activities – maize production and its land
391 area – are main drivers of deforestation in Somalia. Turning to climate variables, 63.3% of variations
392 in average temperature is caused by its own self, whereas 16% is responsible for land under maize
393 cultivation. Additionally, land under maize cultivation causes 23.88% of future fluctuations in
394 average rainfall, whilst average temperature and rainfall – itself – are responsible for 22.79% and
395 33.3% respectively. It is worth noting that maize production is critical for political instability due to
396 that 33.34% variations in political instability is caused by maize production, even though political
397 instability is itself responsible for its highest variations (56.56%).

398 Besides, the IRF results reported in Figure 1 indicate that one standard deviation shock in political
399 instability results in maize production to decrease in the whole 10 periods. This is in line with
400 several studies who found that conflicts undermine investment, infrastructure and agriculture
401 production. Moreover, a one standard deviation shock in rainfall leads to a decrease in maize output
402 from period 2 to period 4.5. From year 4.5 to year 10, the response turns into positive. This
403 corroborates with several studies who reported that rainfall enhances agriculture production.
404 Interestingly, maize production responds negatively in the first 2.5 periods, from 2.5 period the

response turns into positive if one standard deviation shock increase in average temperature. Hence, this contradicts the findings of several studies who concluded that temperature impedes agriculture production. Further, maize output responds negatively for one standard deviation shock in land degradation in the whole periods. Land under maize cultivation exerts a negative effect on maize production in the first 3.5 periods, but from year 4 the response turns into a positive.

Table 7: Variance Decomposition

Variance Decomposition of lnMaize:

Period	S.E.	lnMaize	lnMah	lnLD	lnAVT	lnAVR	PIS
1	0.3698	100.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.4522	92.4405	0.6830	0.3354	4.6294	0.0399	1.8718
3	0.5138	85.1319	1.4478	2.8938	8.6967	0.3800	1.4498
4	0.5387	79.4161	2.0310	4.1142	11.724	0.9900	1.7249
5	0.5561	75.4123	2.177842	3.9618	15.5629	1.0862	1.7989
6	0.5710	71.7940	3.6372	3.7760	17.1588	1.2258	2.4083
7	0.5833	68.8915	5.6160	3.8880	17.1158	1.3015	3.1873
8	0.5946	66.3582	7.6690	4.0678	16.5782	1.3142	4.0126
9	0.6026	64.6610	9.0145	4.1005	16.1452	1.3013	4.7776
10	0.6079	63.5726	9.7000	4.0454	15.9374	1.2948	5.4500

Variance Decomposition of lnMUC:

Period	S.E.	lnMaize	lnMah	lnLD	lnAVT	lnAVR	PIS
1	0.408945	47.88837	52.11163	0.000000	0.000000	0.000000	0.000000
2	0.455903	43.83253	52.36660	3.36E-05	0.447685	0.289740	3.063412
3	0.489888	42.81903	49.00955	2.146529	2.236717	1.119313	2.668867
4	0.500956	41.13833	46.89137	4.425113	2.957151	1.805700	2.782337
5	0.517900	38.58470	45.76830	4.885580	6.374147	1.783887	2.603383
6	0.532412	37.04952	45.71186	4.825807	7.650133	1.921378	2.841298
7	0.545354	35.86694	46.52628	4.684744	7.691091	2.003067	3.227874
8	0.558558	34.51650	47.61152	4.827600	7.354710	1.964583	3.725087
9	0.568343	33.46372	48.34235	4.909217	7.162034	1.905471	4.217199
10	0.574377	32.81743	48.51345	4.860535	7.259678	1.870722	4.678183

Variance Decomposition of lnLD:

Period	S.E.	lnMaize	lnMah	lnLD	lnAVT	lnAVR	PIS
1	0.048777	12.02936	3.650821	84.31982	0.000000	0.000000	0.000000
2	0.064025	22.40852	3.466750	71.78527	0.096496	0.459296	1.783665
3	0.069587	29.47188	4.100763	61.30043	0.090520	1.315934	3.720478

448	4	0.076046	29.84922	8.882671	53.53588	0.899067	1.151729	5.681433
449	5	0.081886	26.60152	13.97783	48.85575	2.666537	1.035661	6.862704
450	6	0.085441	24.54609	14.87834	45.66561	6.062437	0.983931	7.863590
451	7	0.087448	23.43962	14.33274	43.62158	9.320449	0.963879	8.321731
452	8	0.088744	22.76063	14.02820	42.49296	11.32133	0.959496	8.437374
453	9	0.089707	22.27734	14.16893	41.94441	12.24980	0.950758	8.408756
454	10	0.090353	21.97064	14.46174	41.62978	12.63478	0.939986	8.363081

455

456 Variance Decomposition of LAVT:

457	Period	S.E.	lnMaize	lnMah	lnLD	lnAVT	lnAVR	PIS
458								
459	1	0.010350	1.572947	2.316410	2.575126	93.53552	0.000000	0.000000
460	2	0.011405	1.515924	4.272905	3.856730	86.02349	4.249922	0.081031
461	3	0.012020	1.898896	4.341304	4.779002	83.39712	4.231574	1.352103
462	4	0.012995	2.122764	10.97480	6.345762	75.12221	3.632066	1.802402
463	5	0.013541	2.184226	14.26363	6.968799	69.24907	3.472266	3.862009
464	6	0.013866	2.292232	15.58767	7.457040	66.22775	3.351370	5.083938
465	7	0.014057	2.453997	16.24756	7.376625	64.67736	3.262763	5.981696
466	8	0.014160	2.542299	16.25555	7.297928	64.02996	3.216541	6.657720
467	9	0.014234	2.545170	16.11536	7.346406	63.60832	3.196120	7.188625
468	10	0.014288	2.526689	16.00098	7.374177	63.32199	3.181703	7.594455

469

470 Variance Decomposition of lnAVR:

471	Period	S.E.	lnMaize	lnMah	lnLD	lnAVT	lnAVR	PIS
472								
473	1	0.130719	2.669574	15.96628	0.999954	1.088473	79.27572	0.000000
474	2	0.160620	10.39801	20.18439	3.767039	3.772328	55.87401	6.004221
475	3	0.201950	8.933478	22.05199	3.057055	24.99639	36.31226	4.648818
476	4	0.205100	9.133499	21.77622	3.693588	24.37000	35.98597	5.040729
477	5	0.208311	9.019013	21.79964	4.994057	23.87901	35.35181	4.956467
478	6	0.212102	8.708310	22.90763	6.225305	23.15125	34.15843	4.849077
479	7	0.214179	8.684275	23.92059	6.292346	22.72370	33.51563	4.863450
480	8	0.214628	8.659422	23.91270	6.266246	22.76932	33.39307	4.999249
481	9	0.214768	8.649600	23.89426	6.261216	22.79964	33.35309	5.042200
482	10	0.214851	8.642964	23.88130	6.287073	22.79195	33.32746	5.069254

483

484 Variance Decomposition of PIS:

485	Period	S.E.	lnMaize	lnMah	lnLD	lnAVT	lnAVR	PIS
486								
487	1	0.184197	48.95267	0.206749	2.161290	0.013903	0.378169	48.28722
488	2	0.249068	49.54616	0.120383	1.425713	0.008712	0.245274	48.65376
489	3	0.288739	44.78228	0.119760	1.096425	1.350625	1.452757	51.19815
490	4	0.311551	41.80495	0.165777	1.050677	2.329199	1.306763	53.34264
491	5	0.330230	40.28114	0.828810	0.935537	2.646720	1.167159	54.14063
492	6	0.345418	38.18252	0.863427	0.926436	3.758252	1.121578	55.14779

493	7	0.356697	36.51987	0.867226	0.897756	4.838373	1.099207	55.77757
494	8	0.365310	35.22725	0.880774	0.879350	5.749656	1.058146	56.20482
495	9	0.372213	34.20857	0.885155	0.880723	6.548149	1.024042	56.45336
496	10	0.377880	33.34985	0.866757	0.885986	7.331195	0.998798	56.56741
497								
498								

Figure 1: Impulse Response Function

Response of lnMP to MUC

4. Conclusion

Climate change-agriculture sector nexus is topical, where rising temperature and rainfall variabilities have posed a threat on agriculture sector and food security in developing countries. Given that, this study assesses the impact of climate change variables – rainfall and temperature – on maize production in Somalia. Since, maize crop is cultivated mainly in south and central Somalia, and it is worthy noting that this region has been devastated by a long period of political instability. The study incorporates political instability as a main determinant variable of maize production. Johansen and Juselius cointegration, FMOLS, CCR and impact accounting – VD and IRF – were espoused with a time series data spanning between 1980 and 2018. The empirical results of Johansen and Juselius cointegration show that the explanatory variables are cointegrated to maize output in the long-run. Regarding to long-run coefficient parameters of FMOLS and CCR results, average temperature and political instability significantly inhibit maize production in the long-run. Whereas rainfall has a favourable effect on maize production in the long-run. Furthermore, land degradation and land area under maize cultivation – incorporated in the model as control variables – are observed to have positive effects on maize production in the long-run.

Besides, VD revealed that 63.57% of future fluctuations in maize production is explained by historical dynamics in maize production, whereas 9.70% is responsible for land area under maize production. In the same vein, maize production and land area under maize production cause 32.8% and 48.5%, respectively, of future variations in land area under maize cultivation. In addition, 56.56% and 33.34% variations in political instability are caused by itself and maize production, respectively. Regarding to climate variables, 63.3% of variations in average temperature is caused by

its own self, whereas 16% is responsible for land under maize cultivation. Additionally, land under maize cultivation causes 23.88% of future fluctuations in average rainfall, whilst average temperature and rainfall – itself – are responsible for 22.79% and 33.3% respectively. Furthermore, the IRF results indicate that one standard deviation shock in political instability results in maize production to decrease in the whole 10 periods. Moreover, a one standard deviation shock in rainfall leads to a decrease in maize output from period 2 to period 4.5. But from period 4.5 to period 10, the response turns into positive. Interestingly, maize production responds negatively in the first 2.5 periods, if one standard deviation shock increase in average temperature. But from 2.5 period the response turns into positive.

Based on the empirical findings, the study recommends several policy implications. First, possible initiatives are required to be conducted by the government of Somalia regarding to the de-escalation of conflicts. Ensuring friendly political stable environment will enhance agricultural production by rising investment, employment and production. Second, even though climate change-driven by environmental pollution is a global issue, but Somalia policy makers should work with their global partners the fight against rising temperature by reducing environmental degradation – deforestation. Third, ensuring the availability of water can enhance agriculture production; hence, policy makers should implement water irrigation policies such as building dams and storages of water which can be used during periods of precipitation shocks.

Declarations

Data availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Compliance with ethical standards

Ethical approval

Not applicable.

Competing interests

The authors declare that they have no conflicts of interest.

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Reference

- Abbas, S., & Mayo, Z. A. (2021). Impact of temperature and rainfall on rice production in Punjab, Pakistan. *Environment, Development and Sustainability*, 23(2), 1706–1728. <https://doi.org/10.1007/s10668-020-00647-8>
- Adelaja, A., & George, J. (2019). Effects of conflict on agriculture: Evidence from the Boko Haram insurgency. *World Development*, 117, 184–195. <https://doi.org/10.1016/j.worlddev.2019.01.010>
- Ali, S., Liu, Y., Ishaq, M., Shah, T., Abdullah, Ilyas, A., & Din, I. U. (2017). Climate change and its impact on the yield of major food crops: Evidence from pakistan. *Foods*, 6(6), 1–19. <https://doi.org/10.3390/foods6060039>
- Amin, R.M., Zhang, J. and Yang, M. (2015), “Effects of climate change on the yield and cropping area of major food crops: a case of Bangladesh”, *Sustainability*, Vol. 7 No. 1, pp. 898-915, doi: 10.3390/ su7010898
- Arias, M. A., Ibáñez, A. M., & Zambrano, A. (2019). Agricultural production amid conflict: Separating the effects of conflict into shocks and uncertainty. *World Development*, 119, 165–184. <https://doi.org/10.1016/j.worlddev.2017.11.011>
- Ayanlade, A., & Ojebisi, S. M. (2020). Climate change impacts on cattle production: analysis of cattle herders’ climate variability/change adaptation strategies in Nigeria. *Change and Adaptation in Socio-Ecological Systems*, 5(1), 12–23. <https://doi.org/10.1515/cass-2019-0002>
- Chandio AA, Jiang Y, Rehman A, Rauf A (2020) Short and long-run impacts of climate change on agriculture: an empirical evidence from China. *Int J Clim Change Strat Manag* 12(2):201–221. <https://doi.org/10.1108/IJCCSM-05-2019-0026>
- Chandio, A. A., Ozturk, I., Akram, W., Ahmad, F., & Mirani, A. A. (2020). Empirical analysis of climate change factors affecting cereal yield : evidence from Turkey. *Environmental Science and Pollution Research*, 1–14.
- Chandio, A. A., Magsi, H., & Ozturk, I. (2020). Examining the effects of climate change on rice production: case study of Pakistan. *Environmental Science and Pollution Research*, 27(8), 7812–7822. <https://doi.org/10.1007/s11356-019-07486-9>

- Chandio, A. A., Gokmenoglu, K. K., Ahmad, M., & Jiang, Y. (2021). Towards Sustainable Rice Production in Asia: The Role of Climatic Factors. *Earth Systems and Environment*.
<https://doi.org/10.1007/s41748-021-00210-z>
- FAO & World Bank. (2018). *Rebuilding Resilient and Sustainable Agriculture in Somalia - Overview: Vol. I*.
- Guntukula, R., & Goyari, P. (2020). The impact of climate change on maize yields and its variability in Telangana, India: A panel approach study. *Journal of Public Affairs*, 20(3).
<https://doi.org/10.1002/pa.2088>
- Johansen, S. (1988). A statistical analysis of co-integration vectors. *Journal of Economic Dynamics and Control*, 12(2-3), 231-254. [http://dx.doi.org/10.1016/0165-1889\(88\)90041-3](http://dx.doi.org/10.1016/0165-1889(88)90041-3)
- Johansen S, and Juselius K. (1990). Maximum likelihood estimation and inference on cointegration with applications to the demand for money. *Oxford Bull Econom Stat*, 52(1), 69–210.
<http://dx.doi.org/10.1111/j.1468-0084.1990.mp52002003.x>.
- Luhunga, P. M. (2017). Assessment of the impacts of climate change on maize production in the southern and western highlands sub-agro ecological Zones of Tanzania. *Frontiers in Environmental Science*, 5(51), 1–16. <https://doi.org/10.3389/fenvs.2017.00051>
- Migliore, G., Zinnanti, C., Schimmenti, E., Borsellino, V., Schifani, G., Di Franco, C. P., & Asciuto, A. (2019). A ricardian analysis of the impact of climate change on permanent crops in a mediterranean region. *New Medit*, 18(1), 41–51. <https://doi.org/10.30682/nm1901d>
- Mihiretu, A., Okoyo, E. N., & Lemma, T. (2019). Determinants of adaptation choices to climate change in agro-pastoral dry lands of Northeastern Amhara, Ethiopia. *Cogent Environmental Science*, 5(1). <https://doi.org/10.1080/23311843.2019.1636548>
- Pickson, R. B., He, G., Ntiamoah, E. B., & Li, C. (2020). Cereal production in the presence of climate change in China. *Environmental Science and Pollution Research*.
- Porter JR, Semenov MA (2005) Crop responses to climatic variation. *Philos Transact R Soc B: Biol Sci* 360(1463):2021–2035. <https://doi.org/10.1098/rstb.2005.1752>
- Ryan, G., Hussein, H., Nicolas, J., Allison, H., & Paul, P. (2018). On-farm irrigated maize production in the Somali Gu season. *African Journal of Agricultural Research*, 13(19), 969–977.

<https://doi.org/10.5897/ajar2018.13111>

Sarkodie, S. A., & Owusu, P. A. (2017). The relationship between carbon dioxide, crop and food production index in Ghana: By estimating the long-run elasticities and variance decomposition. *Environmental Engineering Research*, 22(2), 193–202.

Shayanmehr, S., Henneberry, S. R., & Sabouni, M. S. (2020). Drought , Climate Change , and Dryland Wheat Yield Response : An Econometric Approach. *Intentional Journal of Enviromental Research and Public Thealth*, 5(17), 5264.

Thornton, P. K., Steeg, J. Van De, Notenbaert, A., & Herrero, M. (2009). The impacts of climate change on livestock and livestock systems in developing countries : A review of what we know and what we need to know. *Agricultural Systems*, 101(3), 113–127.
<https://doi.org/10.1016/j.agsy.2009.05.002>

Warsame, A. A., Sheik-ali, A., Osman, A., & Sarkodie, S. A. (2021). Climate change and crop production nexus in Somalia: an empirical evidence from ARDL technique. *Environmental Science and Pollution Research*, 5(17). <https://doi.org/10.1007/s11356-020-11739-3>

Wheeler, T. and Von Braun, J. (2013), “Climate change impacts on global food security”, *Science*, Vol. 341 No. 6145, pp. 508-513, doi: 10.1126/science.1239402

Xu, H., Twine, T. E., & Girvetz, E. (2016). Climate Change and Maize Yield in Iowa. *PLoS ONE*, 11(5), 1–20. <https://doi.org/10.1371/journal.pone.0156083>

Zhao C, Liu B, Piao S, Wang X, Lobell DB, Huang Y, Huang M, Yao Y, Bassu S, Ciais P, Durand JL, Elliott J, Ewert F, Janssens IA, Li T, Lin E, Liu Q, Martre P, Müller C, Peng S, Peñuelas J, Ruane AC, Wallach D, Wang T, Wu D, Liu Z, Zhu Y, Zhu Z, Asseng S (2017) Temperature increase reduces global yields of major crops in four independent estimates. *Proc Natl Acad Sci U S A* 114(35):9326– 9331. <https://doi.org/10.1073/pnas.1701762114>